GAME THEORY APPROACH TO THE VERTICAL RELATIONSHIPS FOR U.S. CONTAINERIZED IMPORTS

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Game Theory Approach to the Vertical Relationships for U.S. Containerized Imports

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ABSTRACT

Multi-player interactions and vertical relationships in the U.S. containerized-import shipment market are investigated using game theory approaches. Bi-level programming problems (BLPP) are built to capture the hierarchy structure of the container shipping industry, whereas the ocean carriers (OC) are considered as the market leader. For a case study with five players from several levels of the shipment chain, 16 BLPPs are built to analyze the 32 coalition possibilities. Two routes are compared: The West Coast route (WCR) includes one terminal (P1) and one railroad (R); the East Coast route (ECR) includes a second terminal (P2) and the Panama Canal (PC). The impact of Panama Canal expansion is investigated by comparing scenarios with different assumptions of vessel size. Capacity constraints at port terminals are also analyzed by assuming different capacity levels.

The grand coalition of the five players is found to be very unstable because of the unavoidable competition within the coalition; hence, following games are further created, supposing the grand coalition could not form. Model results indicate the OC prefers to form an East Coast Coalition (ECC) with East Coast players if the grand coalition could not form.

Sensitivity analyses on some parameter values for the grand coalition and for the ECC bring some interesting findings. With higher cargo values, the WCR becomes more appealing because of its quicker delivery time and lower inventory costs compared with the ECR. The Panama Canal expansion will improve market power and profit shares for the East Coast players if the canal operator could increase its competitive price more than the increase of costs. Generally, a player will gain more market power if its cost could be reduced. A player's upper bound rate is a reflection of its relative market power. But in a complicated market characterized

with various cooperation-competition strategies and an ambiguous definition of partners and competitors, the impact of a player's upper bound rate on the market power structure could not be easily explained. For future research, the challenge mainly lies on the large number of BLPPs that need to be constructed and solved in order to study more players.

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1. INTRODUCTION

The economic background for this dissertation is briefly discussed first, including the container-shipping market problems, market structures, port competition, and relationships among players along the container shipment chains. Research problems and objectives are introduced in the second section. The organization of the whole dissertation is given in the end.

1.1. Background

1.1.1. Uncertainties in the World Container Shipping Market

There are many issues confronting the container shipping industry: uncertainty in the world economy and international trade, over-capacity caused by orders placed before the economic crisis, fierce competition within the industry (or from outside), etc. Overall, the global container market has been growing fast. Since 2005, the containership fleet has nearly tripled. The world merchant fleet reached almost 1.4 billion deadweight tons (DWT) in January 2011, an increase of 120 million DWT over 2010. New deliveries stood at 150 million DWT, despite approximately 30 million DWT of demolitions and other withdrawals from the market. The surge in the capacity supply makes the competition even harder than it was previously (UNCTAD 2011).

Developments in world seaborne trade and the shipping industry mirrored the performance of the broad world economy. Seaborne trade is subject to the same uncertainties and shocks that may undermine the prospects of a sustained recovery. From 1995 to 2009, the continuing expansion on three major East-West container routes was compelling, followed by a drastic drop in 2009 because of the 2008 world economy downturn. Container carriers decreased their production levels and scrapped old equipment, including ships and container boxes, to cut costs. With the world economic situation brightening in 2010, the seaborne trade volumes recorded a positive turnaround, especially in the dry bulk and container trade segments. In 2010, global container trade volumes bounced back at 12.9% over the 2009 level with a demand surge for almost all trade lanes, which were among the strongest growth rates in the history of containerization. With trade growing at an unexpectedly fast rate, a capacity shortage was observed in the fourth quarter of 2009 and early 2010 (UNCTAD 2011).

Another major uncertainty for U.S. containerized import distribution is the Panama Canal expansion. Currently, the maximum capacity of a ship that could cross the Panama Canal (a Panamax ship) is 4,800 Twenty-foot Equivalent Units (TEU). By the end of 2014, the Panama Canal is scheduled to have completed its greatest expansion, allowing it to handle some of the world's most massive ships. Much bigger ships will be allowed: 50% wider, 25% longer, and a volume of more than 12,000 TEUs. The Panama Canal expansion will have deep, but uncertain, impacts on U.S. ports as well as the U.S. container import and export flow distributions. Many expect a positive impact on the East and Gulf Coast ports, with a slightly negative impact on the West Coast ports because more Asian container ships would divert to the other side of the United States. Many factors may affect the changes. For example, to accommodate bigger ships, state governments and their port authorities along the Gulf and East Coasts are seeking to spend billions of dollars dredging their harbors and increasing the minimum depth from 39.5 feet to 50 feet as quickly as possible. However, U.S. harbor-dredging projects need federal approval and funding, which is an enormously complicated process. On the other hand, there are some observers who do not necessarily agree that the Panama Canal expansion will have major effects on the United States. In a 2010 report, the southern office of the Council of State Governments noted that one school of thought contends that East Coast ports are already struggling to handle loads from smaller ships and would not be able to manage bigger ships even if the ports were technically deep enough. Others doubt that shipping routes would change that drastically because many shippers would still place a premium on speed. Nevertheless, most people still believe the forecast based on the Panama Canal expansion; even if it does not play out in the short term, it definitely will over time (Holeywell 2012).

1.1.2. Market Structure of the Ocean Container-Shipping Industry

Because of the container shipping industry's instability and fierce competition, ship owners and carriers have been making various efforts to minimize the risk and better manage their operations, such as varying the cruising speeds at sea and increasing vessel sizes. During a time of compressed demand, for example, slow steaming could be implemented to cut fuel costs and absorb capacity. A larger vessel size is a classic approach to enhance fuel efficiency, reduce average operating cost, and gain higher market power. Market power is concerned with the ability of firms to secure stronger positions in their market as a means of achieving competitive advantage. Shepherd (1970) defined market power as "the ability of a market participant or group of participants to influence price, quality, and the nature of the product in the market place."

However, for many shipping companies, these individual approaches are not enough for survival; various forms of cooperation agreements, including strategic alliances, mergers, and acquisitions, emerged as the most effective method for this industry. The first cooperative agreement formed by ocean shipping companies was established in the 1870s in an effort to eliminate fierce competition by limiting capacity and fixing freight rates. By 2011, almost all global carriers had been involved in some kinds of global alliances, except for the biggest companies which have a large fleet and a wide service network, such as the Mediterranean

Shipping Company and Maersk Line. Inside the strategic global alliances, various types of collaborative agreements between carriers are also very common, such as fleet sharing and route-services cooperation (Panayides and Wiedmer 2011). And just a few months ago (June 2013), the world's three largest ocean carriers—Maersk Line, Mediterranean Shipping Co., and CMA CGM—stunned the industry when they announced they will form a long-term fleet and cargo sharing alliance (P3 Network) on Asia-Europe, trans-Pacific and trans-Atlantic routes (Journal of Commerce 2013a).

Based on Panayides and Wiedmer's (2011) review, the current literature on alliances for the container shipping industry is rich in qualitative assessment and lacks quantitative evaluations. Franc and Horst (2010) tried to explain why and how shipping lines enlarge their scope in intermodal transport using two approaches: Transaction Cost Economics and Resource-Based View.

Another unique market formation of the shipping industry is called "Conferences." The Conferences are voluntary associations of container lines that agree to abide by fixed rates for a particular trade route in order to stabilize route service (Brooks 1993). The Conferences normally require some form of government approval. The abolition of the exemption from anti-trust rules by the European Union in 2008 has led companies to seek other forms of collaboration instead of the Conference system (Fusillo 2006). The Tioga Group (2007) predicts that Conferences will be of little significance in 10 years and that firms will focus on consolidations instead. It believes the industry is moving to a two-tiered market structure dominated by global container carriers and trade-specific carriers.

Today, the container shipping industry is highly concentrated. The market share for the top 20 liner shipping companies grew to almost 70% of the TEU capacity in January 2011

(UNCTAD 2011). The three biggest carriers, APM-Maersk, Mediterranean Shipping Co., and CMA CGM Group, controlled over 40% of all vessels that are operated by the top 20 shipping lines in 2010 (Panayides and Wiedmer 2011).

The market structure, Conference systems, mergers, acquisitions, and alliances of the ocean shipping industry have important impacts on the container market. However, the market structure for ocean shipping, although noted by many studies, is rarely considered in port-choice models or spatial-economic models for container flow studies (Panayides and Wiedmer 2011).

1.1.3. Inter-Port Competition

World container port throughput increased by an estimated 13.3% to 531.4 million TEUs in 2010 after stumbling briefly in 2009. Severe competition for cargo and ships exists between ports. The seaports increasingly have to deal with large clients who possess strong bargaining power compared with terminal operators and inland transport operators. They are facing the constant risk of losing important clients due to reasons that are largely outside their control. For example, one big client may stop calling at a port because it has rearranged its service networks or has engaged in new partnerships, which may cause the port to lose 10% to as much as 20% of the current container traffic (Notteboom 2007) .

Therefore, in order to attract and retain their clients, port authorities and terminal operators are investing significant funds on port facilities to accommodate the increasing levels of trade and larger vessels, to alleviate congestion, and to enhance their cargo-handling efficiency (Mercator Transport Group 2005, Tioga Group 2007, Hackett 2003). At the national level, investment decisions about port expansion, such as dredging channels and rebuilding piers, need to be made carefully. Economic, environmental, and political factors have to be considered when comparing the nationwide projects. U.S. seaports have to compete for federal approval and funding. For example, the ports of Savannah and Charleston have to compete for a large amount of container movement, and both plan to spend almost $4 billion upgrading harbors, docks, and terminals (Chapman 2012).

1.1.4. Vertical Integration of the Shipment Chain

Major shippers are increasingly expecting one-stop shops to minimize the number of third parties. Port users choose a port-oriented supply chain instead of a single port (Magala and Sammons 2008). Port competition has moved from between ports to between shipment chains. As a result, the worldwide maritime transport chain is perceived as an integrated system.

From the ocean carriers' side, inland logistics are becoming more vital for cost cutting. Actually, about 40% to 80% of the total costs with container shipping are for land-side movements (Notteboom 2004). Although those mega-container vessels continue harvesting economies of scale, they also shift the cost burden from the sea to the land and increase the importance of coordination along the transport chain. More than just cost saving, control of the inland connection is one source of competitive advantage for carriers. Including inland transport services and inland terminals as a pool of internal resources and capabilities strengthens the competitive advantages and market power for shipping companies. Strategic alliances among the shipping companies and coalitions along the shipment chains help firms achieve higher market power (Panayides and Wiedmer 2011).

For that purpose, many ocean carriers have equity interests in stevedoring companies, port terminals, inland trucking or rail connections, as well as in forwarding and warehousing businesses (Brooks 1993). As a result of concentration and vertical-integration activities, many shipping lines are subsidiaries of bigger parent companies, which are able to offer integrated services along the entire supply chain. At the end of the 1970s, Sea-land Cooperation, American

President Lines, and Maersk Lines were the pioneers in providing door-to-door transport services, especially in North America (Hayuth 1987).

However, firms that lack enough volume or capital access may find it hard to enlarge their scopes. Even for those firms that are financially capable, owning equity shares all over the global shipping networks is still difficult to manage. As a result, alliances and contracts with intermodal service providers, container-management service providers, and container-terminal operators are widely applied. These coalitions, although not as tight and reliable as vertical integration within a company, have similar benefits.

1.1.5. Relationships Between Shipping Companies and Other Players

Franc and Horst (2010) summarized three types of cooperation between ocean carriers (OC) and other types of players. The first type is a contract with a risk-bearing commitment signed between an OC and rail companies, barge companies, or combined transport operators. The second type is minority shares owned by OCs in both transport services and inland terminals. The third type is hinterland service subsidiaries of OCs. In the following sub-sections, the typical cooperation practice between the shipping companies and other players in the shipment chain is discussed briefly.

Shipping companies’ investments in terminal management are costly but allow the companies to provide better service (Álvarez-SanJaime et al. 2013). Owning a dedicated terminal could secure berth availability and reliable container flows (Franc and Horst 2010). As for contracts between OCs and the ports, they usually involve fixed payments and/or volume incentives. Because those contracts are usually long term (10-30 years), they limit the flexibility of steamship lines in shifting shipment volumes among the ports (Leachman 2010) .

Railways in North America and trucking companies in Europe have been the target of mergers or strategic alliances initiated by ocean carriers. Leachman (2010) reported that, in the United States, a steamship line typically selected one railroad to contract for hauling all or nearly all its inland point intermodal (IPI) traffic via West Coast ports to Midwestern destinations or to gateways with eastern railroads for further shipment to eastern U.S. destinations. Before 2006, these contracts were typically long term (8-10 years) at favorable rates. The last of legacy long-term contracts between steamship lines and railroads expired in 2011. After the expiration, all lines will have year-to-year contracts with the railroads at higher rates.

Another special type of player in the container-shipping chain is the stevedores. For decades, carriers and stevedores fiercely battled each other when bargaining about contractual arrangements in the key port areas. Negotiations and conflicts between port authorities/operators and stevedoring companies are common in the industry. Soppé, Parola, and Frémont (2009) empirically demonstrated some early forms of partnerships between the two. Early this year (2013), the International Longshoremen’s Association (ILA) and the United States Maritime Alliance (U.S.MX) tentatively made another six-year master contract that covered 14,500 East and Gulf Coast dockworkers after the previous contract expired (Bonney 2012, 2013). In addition to contracts and joint ventures, aggressive takeovers are also used as the quickest way to penetrate a profitable market that has high barriers to entry.

1.1.6. Shipment Chain Structures

The vertical relationship along the shipment links (shippers, ocean carriers, ports, and inland carriers) is much like the one in a supply chain (manufacturers, wholesalers, retailers, and consumers). The similarities between the two include three parts:

1. Upstream and downstream structures. For intermodal shipment, containers are moved from the origin to the destination via different modes in a sequential order. In a typical supply chain, producers sell raw materials to manufacturers who then use the raw materials to produce cargo and sell to wholesalers/retailers. The final product is shipped to final customers by retailers or, sometimes, the wholesalers directly.
2. Inter-chain competition. A supply chain's main function is to transform the raw materials to the final product and to transport it to the final consumers. A shipment chain's main purpose is to transship the cargo from the origin to the destination. The shipment chain may be part of the supply-chain process. No matter if it is a supply chain for a certain product or a shipment chain for a shipper, the core services provided by the same chain type are essentially the same and could be viewed as substitutive goods that compete for the same customers.
3. Intra-chain cooperation and competition. Because of the chain structure and inter-chain competition, it is instinctive for players along the same chain to cooperate as a group in order to compete with other chains. Note that, with companies integrating and enlarging their scope, competition from different echelons also exists. For example, a shipping company operating a terminal will compete with other terminal operators. A wholesaler that also sells directly to individual customers has competition relationships with other pure retailers.

However, an intermodal shipment chain has some additional characteristics that differ from traditional supply chains. For a supply chain, the decision flow is in the opposite direction of product flow (Figure 1.1). The product is passed from lower-level players to a higher level (e.g., retailers to consumers) while the decision is typically made by the higher-level players (e.g., consumers choose retailers.). As for an intermodal shipment chain, the decision direction is not in that order (Figure 1.2). Usually, the customers (shippers or consignees) do not choose specific routes or operators. Instead, the decision is often made by a freight forwarder or an ocean carrier.

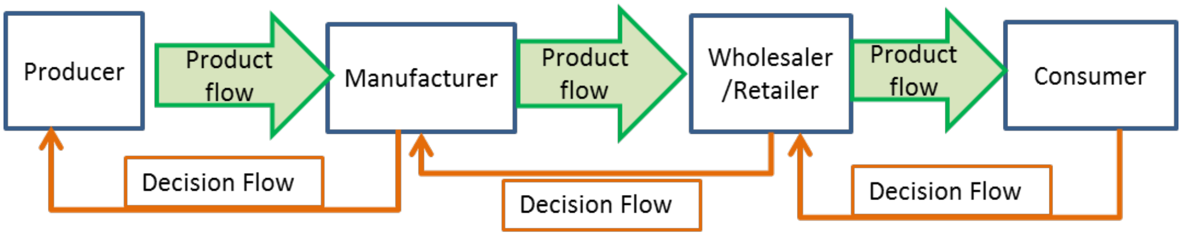

Figure 1.1. Decision Flow and Product Flow in a Supply Chain

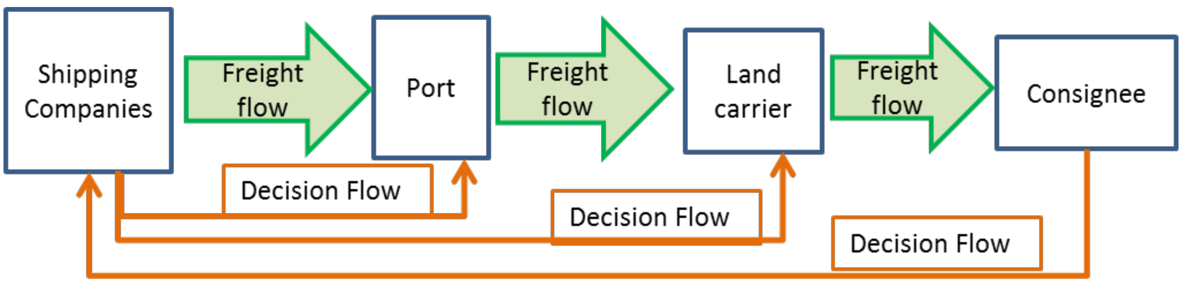

Figure 1.2. Decision Flow and Freight Flow in a Container Shipment Chain

Another special characteristic of intermodal shipments is the geographical restrictions on the terminal operators and some land carriers. Because the geographical locations could be not changed, the choices for partners and competitors are often not flexible. For example, the Los Angeles port could hardly cooperate with the Seattle port because their geographical locations determine that they are natural competitors. For the Asia to U.S. import, West Coast ports could hardly work with the Panama Canal while the Panama Canal may easily establish some kind of cooperation with East Coast ports. A railroad company that has no connection to a port currently could not cooperate with it in the short term.

These special structures of the container-import shipment chain, plus the concentrated shipping industry, together give ocean shipping companies great market power. The containerized import market has a hierarchy structure, and shipping companies are considered as the dominant decision makers in the game.

1.2. Problem Statement and Research Objectives

To model the U.S. containerized import spatial distribution, it is preferential to consider the entire shipment chain instead of only focusing on one node or one link. Compared with a traditional port choice model, which often ignores upper-stream or down-stream logistic segments, an integrated-shipment-chain optimization model could more likely reveal the reasons behind the port choice, of which the port may or may not have control. Such a model could also better predict modal shifting or route changes using sensitivity analysis or stochastic analysis as well as better explain congestions.

However, the single shipment-chain optimization model still misses a critical factor: the interactions of multiple players. Different stakeholders along the chain have different, very often conflicting, economic goals, and they may have cooperation or competition relationships. Their different market powers impact the negotiation process and how the profits/cost savings are divided. The optimal shipment routes, volume, and prices are essentially the equilibrium results of all players' interactions.

The three common methodologies of Freight Network Equilibrium Models, Spatial Price Equilibrium Models, and Integrated Network Equilibrium Models have been extensively used in the freight-modeling literature (Lee et al. 2012). The Integrated Network Equilibrium Models predict freight movements by capturing the behavior and relationship of key stakeholders. However, the model typically involves two agents only: the shipper and the carrier. In this study, the different cooperation-competition relationships of the various players are investigated using game theory solutions.

As the previous section has discussed, the shipment chain has many similar characteristics as a supply chain. In a supply chain, an echelon stands for the group of players at the same level of the chain. Normally, competition exists within one echelon, and cooperation exists between the echelons. The different entities' operational decisions impact each other's profit and, thus, the profit of the entire shipment chain. To effectively model and analyze decision making in such a multi-entity situation where the outcome depends on choices made by every party, game theory is a natural choice.

The purpose of this dissertation is to utilize cooperative game theory to solve the U.S. containerized import shipment optimization problem so that the problem is not only solved as an integrated shipment chain choice, but also as the economic equilibrium resulting from all players' interactions. The players' profit-seeking behaviors may also disturb the market from its equilibrium from time to time. Understanding the behavior of each player and its rationale is critical to modeling the container shipping system. For that purpose, tools from the cooperative game theory are used to understand, predict, and interpret player relationships, shipping route choices, and strategic operational decisions for the complex, multi-agent container shipping system.

The main levels/echelons along the U.S. containerized import chain are as follows: ocean carriers (OC), terminal operators, the Panama Canal operator, and land carriers. Several types of competition and cooperation could be applied as discussed in the Background section. Because the OC acts as the dominant player in the transportation chain, bi-level optimization models could be used to represent the competitive relationship between the first-level, OC-led coalition and the second-level coalition. Various coalitions and competition-cooperation schemes for the main players could be assumed and solved using different bi-level models.

Some key questions that this dissertation strives to answer are as follows: What types of coalitions will be formed? How should the coalition members divide the profit/cost savings? Is the coalition stable? What is the impact of the Panama Canal's expansion? What factors will affect the players' relative market power? What will happen if some key parameter values are changed? This dissertation intends to cast new light onto the U.S. container import market and to inspire new research approaches for future studies.

1.3. Organization of the Dissertation

The remainder of this dissertation is organized as follows: Chapter 2 presents an extensive review of the related literature about containerized import optimal study and game-theory applications in the transportation and supply chain fields, and discusses the advantages and limitations of the different approaches. Chapter 3 presents the methodology of this study, including the preliminaries of cooperative game theory and some classic solution methods. The Bi-level Programming Problems are introduced in the end. Chapter 4 explains how the coalition values are related to bi-level mathematical models and outlines the basic model components, along with different structures for various cooperating schemes. As the complexity of the problem arises exponentially with the number of players, Chapter 5 uses a five-player case study to illustrate how 16 bi-level models are built for 32 coalitions. Chapter 6 presents the results of the case study's four scenarios, including the Shapley values, Least core, and Minmax core solutions. A sensitivity analysis is conducted to analyze the impact of some chosen parameters' values on the model results and cooperative solutions. Chapter 7 continues to present the following games because the grand coalition for the case study is found to be unstable. Sensitivity analysis is conducted, again, for the smaller coalition. Finally, Chapter 8 summarizes the models, results, and findings of this dissertation first, and then points out some study limitations as well as suggestions for solutions and future research directions.

Four appendixes are included at the end. Appendix A lists the 16 models and constraint sets for the case study. Appendixes B and C give the model results for Chapters 6 and 7, respectively.

2. LITERATURE REVIEW OF GAME THEORY APPLICATIONS

This chapter presents a review of existing papers and studies on the containerized import optimal distribution modeling and game theory applications in the transportation and supply chain fields. The benefits of using cooperative game theory (CGT) to consider player interactions are discussed. And the limited applications of CGT to transportation and logistics problems in the current literature are noticed and explained.

Approaches to cargo spatial distribution problems could be grouped into two categories based on the methods used: One type uses optimization modeling and usually ignores the impact of stakeholder interactions. The other type is based on economic equilibrium concepts. In the second group, the studies either implicitly model the competition equilibrium of carriers and shippers, such as Network Equilibrium Models, or explicity evaluate some types of non-cooperative or cooperative strategies. From those studies, it should be noticed that more comprehensive application of non-cooperative and cooperative game theory approaches to freight network planning problems began to merge, although it was at an early stage.

2.1. Optimization Modeling for Containerized Cargo Flows

Most optimization modeling of freight distribution problems focused on one type of stakeholders. They search for optimal shipment routes, volume, or prices, based on the stakeholder's objective functions, such as minimum cost of shipping companies. Some simply try to mimic the observed shipment flow patterns using existing databases and gravity models. Among these papers, only Yang, Low, and Tang (2011) acknowledged there are multiple and conflicting objective functions for different stakeholders; but they utilized goal programming to handle the problem, which essentially implied a perfect cooperation assumption.

Fan, Wilson, and Tolliver (2010) developed a linear optimization model to analyze the intermodal transportation network of containerized imports to the United States. The shipping companies determine optimal flows, ship sizes, ports and rail corridors to minimize cost and meet spatial demands for containers. The included costs are vessel operating cost and rail charges. Later, the model is used to analyze congestion and stochastic impacts on the container shipping network (Fan, Wilson, and Dahl 2012). Other studies on freight network modeling include Southworth and Peterson (2000), who analyzed a multimodal freight transportation network, and Yang, Low, and Tang (2011), who utilized goal programming to handle multiple and conflicting objective functions. The latter study examined the competitiveness of 36 alternative routings for freight moving in East Asia using an intermodal network optimization model. Levine, Nozick, and Jones (2009) developed a linear optimization model to estimate route flows and a corresponding multi-modal origin–destination table for container traffic in the United States. An integrated gravity model was built by synthesizing data from 2004 PIERS dataset on international trade and the 2003 Carload Waybill sample of domestic railcar movements. The origins include 67 foreign countries, while the U.S. destinations are represented by 84 Transportation Analysis Zones. Other similar origin-destination matrix studies include Silva and D'Agosto (2013), who studied the export flow of Brazilian soybeans based on a constrained gravity model.

Jula and Leachman (2011b) also built an optimization model on optimal containerized imports from Asia to the United States from a supply-chain-management point of view. They included inventory cost, in addition to transportation and terminal handling costs, for the importers' total supply chain cost. Mixed supply chain strategies for each importer (direct shipping or consolidation–de-consolidation shipping) were examined. The mixed integer nonlinear programming models were solved by a set of heuristic algorithms. To incorporate the impact of planning time on the decision-making strategies of different stakeholders, they later compared the long-run model to a short-run model (Jula and Leachman 2011a). In the long-run model, the mean and standard deviation of container flow times by channel were fixed, assuming that existing service quality is maintained by ports and carriers in the long term. The short-run model integrated the long-run model with a set of queuing models, which estimates the import container flow times through port terminals, rail intermodal terminals, and rail line-haul channels as a function of traffic volumes, facility conditions, and staffing hours. The short-run model was calculated with iterative runs of the long-run model and the queuing model.

2.2. Freight Network Equilibrium Model and Spatial Price Equilibrium Model

Freight planning models study the freight planning process for shippers and carriers. Each of the two early types of freight planning models focuses on one group only. The Pure Spatial Price Equilibrium Model focuses on the shippers' equilibrium commodity production, consumption, and distribution patterns in spatially separated markets (Samuelson 1952). The Freight Network Equilibrium predicts the modal split and network assignment of freight flows on a general multimodal transportation network. The equilibrium solution should satisfy Wardrop's First and Second Principles (Sheffi 1985). Wardrop's First Principle, also called the user equilibrium (UE), states that, at equilibrium, all used paths between the same origin-destination (O-D) pair for the same commodity have equalized lowest cost. This principle is used for modeling shippers' routing decisions. The modified statement implies that each shipper has no incentive to unilaterally change routes, paths, or modes at equilibrium because it cannot further reduce its cost. Wardrop's Second Principle, also called the system optimum (SO), states that in order to minimize the total transportation cost, all used paths between the same O-D pair for the same commodity have the same lowest marginal cost. This principle applies to the carriers' optimal routing decisions. It is modified to state that, at the optimum, a carrier has no incentive to change its routing plan on the sub-network under its control because it cannot further reduce its cost. In the simultaneous shipper-carrier equilibrium model, the shippers select optimal output, and carriers decide freight rate and shipment route. Both strive to maximize profits.

Hurley and Petersen (1994) used UE principle to model shipper's behavior and SO principle for the carrier. By using a particular form of nonlinear tariff, they showed that the UE and SO can be simultaneously satisfied in an incomplete market. Wie (1995) formulated the dynamic mixed behavior traffic network equilibrium model as a non-cooperative N-person nonzero-sum game. Interactions of two types of players were considered. The first type is called a user equilibrium type, who behaves according to the dynamic user equilibrium principle and requires equal average costs at equilibrium. The second type is called a Cournot-Nash type, who behaves according to the dynamic SO principle and requires equal marginal costs.

The distinction between the Spatial Price Equilibrium (SPE) model and the Freight Network Equilibrium (FNE) model became less prominent and started to converge three decades ago. One example is the Generalized Spatial Price Equilibrium Model (GSPEM) built by Harker and Friesz (1986a, b), and which provided an explicit treatment of shippers' and carriers' behaviors using Wardrop's two principles, and solved the shippers' and carriers' problems simultaneously by assuming the marginal cost pricing principle.

Freight Network Equilibrium Models based on Wardrop's two principles are essentially one type of Nash Equilibrium models. More complicated relationships in the transportation planning problem are investigated later by other researchers using Nash Equilibrium models or cooperative game models. In the following sections, those studies are presented according to their application fields.

2.3. Game Theory Application in Ocean Shipping Industry

Yang, Liu, and Shi (2011) studied the economic performance and stability of shipping liner alliance by applying core theory where business cooperation is partly realized by delivering joint-service with mega container ships. Compared with non-cooperative games, core theory aims to solve problems when players decide to cooperate with tight binding agreements for achieving their joint objectives.

Examples of game theory application in the port industry include Saeed and Larsen (2010), who examined the effects of cooperation in the context of port competition in Pakistan, and Ishii et al. (2013), who examined how each port selects port charges strategically in the timing of port capacity investment by constructing a non-cooperative game theoretic model. Saeed and Larsen (2010) discussed a two-stage game that involves three container terminals located in Karachi Port in Pakistan. The first stage is a cooperative game whereas the terminals have to decide whether to act as a singleton or to enter a coalition. The second stage is modeled as a Bertrand game with the coalition competing with the terminal in Karachi Port (if any) that has not joined the coalition by choosing their optimal prices. Thus, three partial coalitions and one grand coalition are investigated. Although the authors tried to use the concepts of “characteristic function” and “core” to analyze each coalition’s stability, they actually used the first order condition of the grand coalition’s profit function to find equilibrium price and profit for each terminal. (This approach may be right to get the Nash equilibrium for the Bertrand game, but questionable for a cooperative game.) Ishii et al. (2013) constructed a non-cooperative model with stochastic demand for two ports that compete with each other, in order to find how the other port should respond in setting prices if a port invests in its capacity and how equilibrium port charges are determined under demand uncertainty. The Nash equilibrium is derived and propositions are applied to the case of inter-port competition between the ports of Busan and Kobe.

For relationships between different types of players in the ocean shipping market, Lee et al. (2012) modeled the interactions of the three types of players in an oligopoly shipping market: ocean carriers, land carriers, and port terminal operators. In the three-level non-cooperative model, they used Nash Equilibrium to find optimal decisions for each player. The ocean carrier is regarded as the leader, while port terminal operators are the followers to the ocean carriers and the leaders to the land carriers. At the upper-level interaction, port service charges affect ocean carriers' route choices while ocean carriers' routing decisions determine port throughput. Ocean carriers choose a port terminal based on factors including port location, service charge, and inland connections. At the lower-level interaction, service demands of land carriers are determined from the port throughputs. Each type of carrier has an objective function of maximizing profit. They utilized the Variational Inequality (VI) method to get the Nash Equilibrium solution.

Asgari, Farahani, and Goh (2013) developed a game theoretic network design model that considers three scenarios: 1) Perfect competition exists between the hub ports, and shipping companies only choose one hub port; 2) Perfect cooperation exists between the hub ports; 3) And grand cooperation exists among the shipping companies and the hub ports. The shipping companies are considered as the market leader while the two relay hub ports are followers of the shipping companies, and are competing to capture more market share from the shipping companies. At the first level, the shipping companies choose the cheapest path. At the next level, the hub ports strive to maximize revenue. An interval branch and bound was designed to solve the non-convex nonlinear integer programming model. The scenarios were tested using empirical data from two leading Asian hub ports: Singapore and Hong Kong.

Talley and Ng (2013) proposed a Nash non-cooperative equilibrium model to determine the maritime transport chain choice by water carriers, inland carriers, ports, and shippers. They stated that a simultaneous solution to the four individual optimization problems for the four players gives rise to a real maritime transport chain choice.

2.4. Game Theory Application in Transportation

For more general transportation studies, Adamidou and Kornhauser (1993) formulated an *N*-person non-cooperative game to solve a railroad freight car management problem. Hong and Harker (1992) used a Nash Equilibrium model to develop proper pricing of landing slots with given demand and airport capacity. Variational Inequality formulation is used to solve the oligopolistic air transport market model. Castelli et al. (2004) considered a strategic game between two players on the same road transportation network, and introduced a bi-level linear programming formulation for the problem. The first player aims at minimizing transportation costs, whereas the second player aims at maximizing profit. A bi-level model was also used by Moreno-Quintero, Fowkes, and Watling (2013), who analyzed the interactions between the road freight carrier and the road planning authority. Shiao and Hwang (2013) analyzed the competitive strategies of air cargo carriers in the Asian markets through a two-stage, Nash best-response game.

Wang (2002) studied the shipper and carrier relationship using a bi-level program, where at the first level, oligopolistic carriers make pricing and routing decisions; and at the second level, the shippers make production and consumption decisions based on spatial price equilibrium principle. Based on whether the oligopolistic carriers collude or compete with each other, the first-level problem is formulated as either an optimization problem or a Variational Inequality problem. A sensitivity analysis-based heuristic algorithm is proposed to solve the program. The author did not consider the different cooperative schemes between the carriers and shippers, or among the shippers themselves.

Xiao and Yang (2007) investigated the competitive equilibrium in an oligopolistic freight market with shippers, carriers, and infrastructure companies (IC). All three kinds of players act as profit maximizing agents, except that the carriers and ICs are assumed to behave cooperatively in their own coalitions. A three-stage game model is built. First, the ICs decide on a tariff to the carriers, according to their own cost function and the information they have about the shipper and the carriers. Then the carriers determine another tariff to the shipper, according to their own cost function, the tariff given by the ICs, and the information they have about the shipper. Finally, the shipper decides the quantity of the production to maximize its own profit. They modeled this hierarchy decision-making process as a strengthening of the Nash equilibrium known as sub-game perfect Nash equilibrium. Their results showed Nash Equilibrium flows will also be system optimum, if nonlinear tariff schedules are applied by both the carriers and infrastructure companies. The division of the surplus associated with each shipment is obtained by solving a linear programming problem.

Cooperative game theory approach is used much more commonly on horizontal coordination. Cost savings and profit sharing are both common goals of those studies. Some of them compared different allocation approaches. Some proposed new cost or profit allocation methods.

Krajewska et al. (2008) use the Shapley value for sharing the cost savings when freight carriers cooperate to balance their request portfolios, reduce the number of empty truck movements, and achieve substantial cost reductions. The carriers faced the problem of optimally serving a set of pickup and delivery requests with time windows (PDPTW). They also checked the non-emptiness of the core and eventually whether the Shapley value belongs to the core.

Frisk et al. (2010) studied a collaborative forest transportation planning problem for eight forest companies in southern Sweden and investigated a number of sharing mechanisms based on economic models, including Shapley value, the nucleolus, methods from Tijs and Driessen (1986) (ECM, ACAM, CGM), and methods based on shadow prices and volume weights. They also proposed a new allocation method, Equal Profit Method (EPM), which is stable in the way that the maximum difference in relative savings between all pairs of two players is minimized (the participants' relative profits are as equal as possible.)

Audy, D'Amours, and Rousseau (2011) presented a collaborative transportation case for shippers in the furniture industry and proposed two modifications to the Frisk et al. (2010) EPM method, as well as a modified Alternative Cost-Avoided Allocation Method (ACAM) presented in Tijs and Driessen (1986), to better reflect the furniture industry's business context. The ACAM method was used to allocate the additional cost incurred by special planning requirements of different companies.

Liu, Wu, and Xu (2010) examined carrier alliances with backhauling and lane exchanges to reduce costs and increase profitability. They used different cooperative game solutions, such as the Shapley value and the nucleolus, and also proposed a new cost savings allocation method called Weighted Relative Savings Model (WRSM), which minimizes the maximum difference between weighted relative savings among participants.

Sherali and Lunday (2011) found some deficiencies in the present allocation scheme for apportioning a railcar fleet to car manufacturers. Four alternative schemes to apportion railcars to shippers were analyzed; and two railroad allocation schemes were proposed. Of the eight alternatives, the authors found the combination of methods based on Shapley value was appealing because of approach uniformity.

Cruijssen et al. (2010) proposed a new procedure of supplier-initiated outsourcing (called insinking), and used the Shapley Monotonic Path of customized tariffs to allocate synergies among shippers in a fair and sustainable way. These customized prices were based on each shipper's actual contribution to the total synergy and accomplished a fair allocation of the monetary savings resulting from the cooperation. The procedure used an operations research algorithm to calculate the value of every possible shipper's coalition, and used a game theoretical solution concept to construct the customized tariffs. The authors found that the insinking is not only a viable alternative of traditional shipper outsourcing approach, but also has certain advantages.

Lozano et al. (2013) presented a linear model and used it to study the cost savings that different companies may achieve when they merge their transportation requirements. Because the core is very large in their case study, they tested another four methods: the Shapley value, the Minmax core, the Least core (LC), and the τ-value. It showed all methods give similar (stable and fair) solutions, but LC and Minmax core are preferred because of their relative simplicity and their seeking fairness. Chen and Yin (2010) found that for a group buying game with a linear quantity discount schedule, the uniform allocation resulted in the same cost allocation solution from the Shapley value. They concluded that simple allocations, such as the uniform allocation, will violate the Shapley axioms for some games but still coincide with the Shapley value in specific games. Considering the main drawback of the Shapley value—the complexity of its computation, especially in the voting game whose Shapley value computation is #p-complete—Fatima, Wooldridge, and Jennings (2008) developed a new linear approximation algorithm based on randomization to overcome the complexity of computing the Shapley value for voting games. Their method has linear time-complexity with the number of players, but has an approximation error that is, on average, lower than a multi-linear extension method.

2.5. Application of Cooperative Game Theory to Supply Chain Management

Many cooperative actions, such as collaborative planning, capacity sharing, and information sharing, are popular in supply chain management. The importance of supply chain coordination and benefits has motivated more studies on supply chain cooperation and competition problems and applications of game theory to this field in recent years (Cachon and Netessine 2004, Arshinder, Kanda, and Deshmukh 2008).

Most studies on supply chain cooperation focused on cooperation between players in the same echelon. Nagarajan and Sosic (2008) did a survey on application of cooperative game theory to supply chain management. Among the 80 papers they reviewed, most are studies on cooperation in the same echelon. For this study, several papers on multi-echelon collaboration in supply chain management are found and introduced as follows.

Bartholdi and Kemahlioglu-Ziya (2004) considered the inventory-pooling coalitions of two retailers and one common supplier, whereas the supplier bears all the inventory risk. They found the Shapley value allocations may be perceived as unfair in that the retailers' allocations can exceed their contribution to supply chain profit in some situations.

Huang, Huang, and Newman (2011) considered the coordination of suppliers and components selection, pricing, and replenishment decisions in a multilevel supply chain composed of multiple suppliers, one single manufacturer, and multiple retailers. This coordination problem was modeled as a three-level dynamic non-cooperative game model. Analytical and computational methods were developed to determine the Nash equilibrium of the game.

Özener and Ergun (2008) proposed several cost-allocation schemes based on cooperative game concepts, such as efficiency, stability, and cross monotonicity. They also defined several new properties for their problem. The allocation schemes were applied to a logistics network in which shippers collaborate and bundle their shipment requests to negotiate better rates with a common carrier.

Rosenthal (2008) studied the cooperation within one vertically integrated supply chain that has three divisions. The goal was to find the best way of allocating costs and profits among the divisions for a multi-echelon organization. The authors found the Shapley value generates a fair solution only in the perfect information case. Therefore, they used a linear program to obtain cooperation solutions for the asymmetric information case. When the divisions in the supply chain add value to the product and do not create technological or transactional inefficiencies, the author showed that the game is convex, meaning that the core is always nonempty and that the Shapley value allocation always lies in the core. But for the integrated supply chain in the vertical organization, the characteristic function will not necessarily be a superadditive profit function or subadditive cost function, since inefficiencies may occur due to forced cross-divisional cooperation.

Some other studies include: Zheng et al. (2011), which modifies the Shapley value method to solve the allocation problem of the closed-loop supply chain that includes one manufacturer, one distributor, and one independent recycler; Wang, Guo, and Efstathiou (2004), which analyzed non-cooperative behavior in a one-supplier-N-retailer supply chain; and Zhao et al. (2010), which took the cooperative game approach to consider option contracts as a coordination solution between manufacturers and retailers.

Other than transportation and supply chain management, game theory applications include fields like emission reduction problems (Filar and Gaertner 1997, Bahn et al. 1998, Petrosjan and Zaccour 2003), the automotive industry (Cachon and Lariviere 1999, 2005), retail (Sayman, Hoch, and Raju 2002), telecommunications (Nouweland et al. 1996, Anandalingam and Nam 1997), aviation (Adler 2001), and health care (Ford, Wells, and Bailey 2004).

2.6. Conclusions of Literature Review

Based on the literature review, it is evident that more applications of game theory have emerged in the transportation and supply chain analysis. But most of them used Nash Equilibrium to capture the impact of competing relationships on the economic equilibrium. Some of those also used multilevel programming programs to examine the hierarchy relationships. Very rarely were the cooperative approaches utilized. When cooperative games are concerned, very few papers are found using advanced solution concepts, such as the Shapley Value and the core, especially for vertical cooperation. Most analyses of transportation cooperation focused on one type of stakeholders, e.g., shippers or carriers. Vertical collaboration in supply chain studies exists but is limited to the simplest cases.

Among a limited number of studies that did encounter different echelons' interactions, Lee et al. (2012) utilized the Variational Inequality method to get the Nash Equilibrium solution for a non-cooperative model with three types of players in the ocean shipping market. Lin and Hsieh (2012) also used a cooperative game approach to study a three-echelon supply chain coalitional game, whereas inter-chain competition and intra-chain cooperation are both examined.

Asgari, Farahani, and Goh (2013) analyzed three types of interactions between a shipping company and two hub ports, but did not use any game theory solutions. Rosenthal (2008) study used Shapley value and cooperation theory to analyze cooperation among players at different levels of one vertically integrated supply chain.

There are at least two reasons for this lack of research applying cooperative game theory approach to freight shipment distribution. First, Nash Equilibrium and Wardrop Principles have been well developed and extensively used. Therefore, most research on transportation spatial distribution problems tend to use the most traditional methods, which have been relatively successful and widely accepted. Second, as discussed the first chapter, the structure of a shipment chain resembles the one of a supply chain, with different levels of players. The intra-chain cooperation and inter-chain competion characters make the problems difficult to model. So far, as much review has been done, although many studies have noted the necessity of considering player interactions in supply chain management problems, analytical analysis of multi-echelon players' cooperation is very limited, or only include a very small number of players. For a shipment distribution analysis, typically a large number of nodes, arcs and players are involved. It is a challenge to model such a complex system using a cooperative game theory approach.

3. METHODOLOGY

3.1. Preliminaries of Cooperative Game Theory

"Game theory can be defined as the study of mathematical models of conflict and cooperation between intelligent rational decision-makers. Game theory provides general mathematical techniques for analyzing situations in which two or more individuals make decisions that will influence one another's welfare" (Myerson 1991). It deals with interactive optimization problems (Cachon and Netessine 2004). John von Neumann and Oskar Morgenstern established and summarized the basics of game theory, and have been credited as the fathers of modern game theory. The subject of cooperative games also first appeared in their seminal work (von Neumann and Morgenstern 1944). However, for a long time, cooperative game theory (CGT) did not enjoy as much attention as non-cooperative game theory. Papers employing CGT to study supply chain management and transportation problems had been scarce, although becoming more popular (Cachon and Netessine 2004). This chapter's purpose is to give a brief introduction to CGT and a summary of those concepts that are most relevant to this dissertation.

3.1.1. Introduction of CGT

Though different in theoretical content and the methodology used, the cooperative and the non-cooperative approach are looking at the same problem. To quote the words of Aumann (1959), "the game is one ideal and the cooperative and non-cooperative approaches are two shadows." In a non-cooperative game, each player selects a strategy that maximizes its payoff, assuming others' strategies could be expected and defensive strategies are applied by everyone. CGT involves a major shift in paradigms compared with non-cooperative game theory: while the latter is more concerned with the specific actions of the players, the former focuses on the outcome of the game instead of individual actions (Cachon and Netessine 2004). The CGT assumes that the players negotiate before the game is played and make a “binding” agreement. Once a coalition is formed, the players of the coalition act as one player with a jointly agreed set of strategies to maximize the sum of payoffs to the coalition (Thomas 1986). After this comes the problem of sharing the rewards among members of the coalition. Each individual would join the coalition that offers the greatest reward. So another assumption about cooperative games is that the players can transfer their gains between each other via “side payment” without any transaction losses.

Two distinctive approaches are used to examine solutions in cooperative games. The first solution concept is based on the domination of one set of outcomes, characterized by payoff vectors, over others. The dominant set is supposed to be in the “core.” Another way of obtaining solutions for cooperative games is to consider values, including the Shapley value, which provides a unique outcome for a cooperative game. The core and the Shapley value are only two of the many solution concepts for coalition games with transferable utility, but also the most classic ones. Almost all cooperative game solutions use the characteristic function to select a subset of imputations that satisfy the requirements embodied in the solution concept adopted. An imputation is a vector whose entries correspond to players’ payoffs. The definitions of characteristic function and imputation are introduced first.

Definition 1: A **characteristic function** of an n-person game assigns each subset S of the players the maximum value of $v(S)$ that coalition S can guarantee itself by coordinating the strategies of its members, no matter what the other players do. (Thomas 1986)

The coalition value *v(S)* could also be called the **worth** of coalition *S*. Note by definition the value of a coalition is independent of the coalitions and actions taken by the non-coalition members.

Definition 2: An **imputation** in an *n*-person game with characteristic function *v* is a vector $x = (x_1, x_2, \dots, x_n)$ satisfying

1) $\sum_{i=1}^{n} x_i = v(N)$; (3.1)

2) $x_i \geq v(i), for\ i = 1,2, \dots n$ (Thomas 1986). (3.2)

The first condition (Efficiency Condition) requires that total repay to all the players in the game should equal to the grand coalition's value, and is a Pareto optimality condition. The second condition (Individual Rationality Condition) means that everyone must not get less than he could get if he played by himself.

3.1.2. The Core

Gillies (1959) defined the core based on the idea that a good imputation should not be dominated by any other imputations; otherwise it is not stable. The definitions of domination and the core are introduced below.

Definition 3: Let *x* and *y* be two imputations. Imputation *x* dominates *y* over coalition *S* ($x >_s y$) if

1) $x_i > y_i\ for\ all\ i \in S$; (3.3)

2) $\sum_{i \in S} x_i \leq v(S)$ (Thomas 1986). (3.4)

Definition 4: The core of a game *v*, denoted by *C(v)*, is the set of imputations that are not dominated for any coalition (Thomas 1986).

Theorem 1: Imputation *x* is in the core if and only if

1) $\sum_{i=1}^{n} x_i = v(N)$, (3.5)

2) $\sum_{i \in S}^{n} x_i \geq v(S), for\ all\ S \in N$ (Thomas 1986). (3.6)

This theorem tells that "a utility vector is in the core if the total utility of every possible coalition is at least as large as the coalition's value, i.e., there does not exist a coalition of players that could make all of its members at least as well off and one member strictly better off" (Cachon and Netessine 2004). Thus, if a feasible allocation *x* is not in the core, there is a coalition *S* such that the players in *S* could all do strictly better than in *x* by cooperating together and dividing the worth *v(S)* among themselves.

There have been some applications of core theory in the shipping industry in the past (Sjostrom 1989, 1993, Pirrong 1992, Yang, Liu, and Shi 2011). Sjostrom (1989, 1993) indicates that the reason for collusion in the liner market is to impose equilibrium where non-empty core exists. He proves that empty core is more likely to appear in liner shipping markets where carriers' minimum average costs demonstrate limited variability, demand is less elastic, and the excess capacity exists. He also recognizes that inefficient entry is the main cause for an empty core to occur in the liner shipping market.

Although the core restricts the amount of allocations that are stable and reasonable, it does not give a definite solution (there are often many imputations in the core.) It is also very often that the core is empty, which indicates that the grand coalition is not stable, i.e., some players may break out and start their own coalition. Thus another approach of solving the cooperative game is a unique expected payoff allocation for the players.

3.1.3. The Shapley Value

Lloyds S. Shapley put forth three axioms which he believed each player's payoff in a superadditive game should satisfy, and he proved there is only one function that will satisfy all of them (Shapley 1953). The three properties are: 1) Symmetry: Only the role of a player in the game should matter, not the player's specific names or label in the set N; 2) Dummy/efficiency: Only players that "add value" will receive positive allocations and they should divide the grand coalition's value among themselves, allocating nothing to the dummies; 3) Additivity: the Shapley value added from two separate games is equal to the value from the sum of the two games. The superadditive game is defined as below.

Definition 5: A characteristic function *v* is said to be **superadditive** if and only if, for every pair of coalitions *S* and *T*,

$$if\ S \cap T = \emptyset\ then\ v(S \cup T) \geq v(S) + v(T). \tag{3.7}$$

The function $\emptyset_i(v)$ that satisfies all the three axioms is the Shapley value payoff to the i^{th} player. The formula is given as Equation 3.8.

$$\emptyset_i(v) = \sum_K \big(v(K) - v(K \setminus \{i\})\big) \frac{(k-1)!(n-k)!}{n!} \tag{3.8}$$

The formula could be interpreted as follows. The players are assumed to arrive at the game in a random order. There are totally *n* players. When player *i* arrives, he gets the extra amount value (revenue increase or cost saving or both) he brings to the game, which is *v(K)* – *v(K*$\{i\}$*)* assuming there are *K-1* players ahead of him. The probability that player *i* arrives after any *K-1* players and before any other *n-S* players could be calculated as $(k-1)!\,(n-k)!/n!$. So the Shapley value for a player is essentially the weighted average of the contributions the player makes to all possible coalitions, while the weight depends on the number of players *n* and the number of members in each coalition (Myerson 1991). If the game *v* is superadditive, then the Shapley value must be individually rational, in the sense that $\phi_i(v) \geq v(\{i\}), \forall i \in N$.

Although the Shapley value's formulation depends on the function *v* being superadditive, Aumann and Shapley (1974) showed a small technical modification will generalize the Shapley value to nonsuperadditive games. For games that are not superadditive, one can replace the "additivity" condition (3) with the following "linearity" condition: that a reasonable allocation should give a player in a convex combination of games the convex combination of the allocations from the separate games. When taken along with axioms (1) and (2), linearity amounts to the same thing as additivity.

Definition 6. In general, let *(N,v)* be a superadditive game for which *v(S)* is nonnegative for all $S, T \subseteq N$, with $v(\emptyset) = 0$, *(N,v)* is a **convex game** if

$$v(S \cup T) + v(S \cap T) \geq v(S) + v(T), \forall\, S, T \subseteq N \tag{3.9}$$

Shapley (1971) showed that if *(N,v)* is convex, then (2) is equivalent to the condition known as the "increment property," namely,

$$v(S \cup \{i\}) - v(S) \leq v(T \cup \{i\}) - v(T), \forall\, i \in N, S \subseteq T \subseteq N\{i\} \tag{3.10}$$

This property represents a "bandwagon" effect in which all players contribute a non-decreasing marginal profit as the coalitions they join increase in size. Shapley (1971) showed that the core of a convex game is always nonempty and the Shapley value of the game is the centroid of the core.

In comparison to the core, the Shapley value has attracting properties of being unique and fair, and it always exists. But by itself there is no guarantee that it is stable, e.g., it may not be part of the core. So far, the Shapley value is considered a superior solution to dynamic coalitions, and has been a powerful tool for evaluating the power structure in a coalitional game. It is probably the most commonly used solution method in the literature. But due to its computation complexity and that it may not be stable, many other approaches have been proposed to modify it or approximate its results.

3.1.4. Least Core and Minmax Core

Two of the methods that have been proposed to handle two limitations of core solution—it is not unique and it may be empty—are Least core (LC) (Drechsel and Kimms 2010) and Minmax core (MMC) (Drechsel and Kimms 2011) .

The strong ε-core was introduced by Shapley and Shubik (1966) as

$$C_\varepsilon(c) = \{y \in R^n : \sum_{i \in N} y_i = v(N) \text{ and } \sum_{i \in S} y_i \geq v(S) - \varepsilon \ \ \forall S \neq \emptyset, S \subset N\} \tag{3.11}$$

Maschler, Peleg, and Shapley (1979) defined LC as being the strong ε-core with smallest possible $\varepsilon \in \mathcal{R}$ such that $C_\varepsilon(c)$ is not empty. Hence, they described the LC as centrally located within the core, if the core is not empty; and as a means to reveal the position in the "latent" core, if the core is empty.

The formulation of the Least core (LC) method is shown as follows.

$$\min \varepsilon \tag{3.12}$$

Subject to

$$\sum_{i \in N} y_i = v(N) \tag{3.13}$$

$$\sum_{i \in S} y_i \geq v(S) - \varepsilon \tag{3.14}$$

A value of $\varepsilon \leq 0$ indicates the core is not empty.

Analogously, the η-core of a game and the corresponding Minmax core (Drechsel and Kimms 2011) can be defined respectively as

$$C_\eta(c) = \{y \in R^n : \sum_{i \in N} y_i = v(N) \text{ and } \sum_{i \in S} y_i \geq \eta v(S) \ \ \forall S \neq \emptyset, S \subset N\}; \tag{3.15}$$

$$\eta_0 = \max\{\eta : C_\eta(CS) \neq \emptyset\}. \tag{3.16}$$

The formulation of the Minmax core (MMC) method is shown as follows.

$$Max\ \eta \tag{3.17}$$

Subject to

$$\sum_{i \in N} y_i = v(N) \tag{3.18}$$

$$\sum_{i \in S} y_i \geq \eta v(S) \tag{3.19}$$

A value of $\eta \geq 1$ indicates that the core is not empty.

3.2. Stackelberg Game and Bi-Level Programming Problem

3.2.1. Stackelberg Game and Hierarchy Decision Making by BLPP

Stackelberg (1934) introduced a dynamic game called the Stackelberg game. In this game, one player acts as the leader and chooses a strategy first. The follower observes this decision and makes its strategy choice after the leader. The leader-follower model has been used in literature to model the hierarchy relationship between policy makers and transportation practitioners, or between infrastructure planners and users. It also appeared multiple times in studies to model shipping companies as the dominant decision maker and the leader in the container shipping industry while other players are considered as followers (Lee et al. 2012, Talley and Ng 2013, Asgari, Farahani, and Goh 2013, Xiao and Yang 2007, Wang 2002).

The leader-follower game is a typical hierarchy decision-making problem, which is most properly represented by a special type of mathematical programming: bi-level or multilevel programming models. A bi-level math programming is one that the constraint region contains another optimization problem. A three-level problem results when the second level problem is another bi-level problem itself. Multilevel problems could be further defined by extending this idea.

To define the problem, suppose there are *n* optimizers, each of which wishes to maximize its objective function f_i. Each optimizer has control over a set of decision variables $X_i \subseteq R^n$. Optimizer 1 to *i* makes choices in a sequential order. The whole problem could be represented in the following format:

$$\max f_1(x^1, x^2, \ldots, x^n), where\ x^1 solves \tag{3.20}$$

$$x^1 \in X^1 \tag{3.21}$$

$$g^1(x^1) \geq 0 \tag{3.22}$$

$$\max f_2(x^1, x^2, \ldots, x^n), where\ x^2 solves \tag{3.23}$$

$$x^2 \in X^2 \tag{3.24}$$

$$g^2(x^1, x^2) \geq 0 \tag{3.25}$$

...

$$\max f_n(x^1, x^2, \ldots, x^n), where\ x^n solves \tag{3.26}$$

$$x^n \in X^n \tag{3.27}$$

$$g^n(x^1, x^2) \geq 0 \tag{3.28}$$

If n =1, the problem becomes a standard optimization problem. If n = 2, this is a bi-level problem. Fortuny-Amat and McCarl (1981) pointed out that although most managerial decisions are of a bi-level or multilevel nature, many problems are not studied in the multilevel framework when they should have. Instead, either multi-objective programming or a procedure that ignores the sub-problem objective was used. In the case of multi-objective programming, the objectives are weighted and optimized simultaneously, which introduces irrational economic behavior and, in fact, models the wrong problem. On the other hand, ignoring the sub-problem's objective will also introduce large errors in the master optimal objective.

3.2.2. Solution of BLPP

Bi-level programs were initially called *mathematical programs with optimization problems in the constraints* by Bracken and McGill in a series of papers (Bracken and McGill 1973, 1974, 1978). The term bi-level and multilevel programming were first used by Candler and Norton (1977). The first bibliographical survey on the subject was written by Kolstad (1985).

Surveys presenting both theoretical results and solution approaches include Vicente and Calamai (1994) and Colson, Marcotte, and Savard (2007).

Being generically non-convex and non-differentiable, bi-level programs are intrinsically hard. Even the “simplest” instance, the linear-linear BLPP, was shown to be strongly NP-hard (Hansen, Jaumard, and Savard 1992, Vicente, Savard, and Júdice 1996). Thus, it is not surprising that algorithmic research to date has focused on the simplest cases of bi-level programs, such as those with linear, quadratic, or convex objective and constraint functions. In fact, the most studied bi-level programming problems have been for a long time the linear BLPP (Colson, Marcotte, and Savard 2007).

One type of algorithm for BLPP is the extreme point search method, which focuses on linear bi-level problems. A linear bi-level problem with a finite optimal solution contains at least one vertex of the constraint region where an optimal (global) solution is attained (Shi, Lu, and Zhang 2005). Another type of algorithm for bi-level programming problems when the lower level problem is convex and regular utilized Karush-Kuhn-Tucker conditions to transform the problem into a single-level problem. For a standard maximization model below, the Lagrangian function combines all constraints and the objective function. The necessary conditions for this function’s minimum are the same as those for the constrained original problem. For a model defined by Equation 3.29 to 3.31, the Lagrangian function of it is shown by Equation 3.32. And by taking the first derivatives of the Lagrangian function, the Karush-Kuhn-Tucker (KT) conditions of the model are obtained as Equations 3.33 to 3.38.

$$\max f(x) \tag{3.29}$$

Subject to

$$g_i(X) \geq 0, i = 1, \dots, m \tag{3.30}$$

$$h_i(X) = 0, i = 1, \dots, p \tag{3.31}$$

$$L(x, u, v, s) = f(x) + \sum_{i=1}^{m} u_i[g_i(x) - s_i^2] + \sum_{i=1}^{p} v_i h_i(x) \tag{3.32}$$

$$\nabla f(x^*) + \sum_{i \in Active} u_i \nabla g_i(x^*) + \sum_{i=1}^{p} v_i \nabla h_i(x^*) = 0 \tag{3.33}$$

$$g_i(x^*) - s_i^2 = 0, i = 1, 2, \dots, m \tag{3.34}$$

$$h_i(x^*) = 0, i = 1, 2, \dots, p \tag{3.35}$$

$$u_i g_i(x^*) = 0, i = 1,2, \dots, m \tag{3.36}$$

$$s_i^2 \geq 0, i = 1,2, \dots m \tag{3.37}$$

$$u_i \geq 0, i = 1,2, \dots m \tag{3.38}$$

After KKT transformation, the problem becomes a single-level programming problem, but contains a set of nonlinear complementary slackness constraints, which are intrinsically combinatorial. When the first-level problem is convex, the new problem is best addressed by enumeration algorithms, such as branch-and-bound (BB). Algorithms based on this idea were proposed by Bard and Falk (1982) for solving linear bi-level programming problems. The approach was adapted by Bard and Moore (1990) to linear-quadratic problems and byAl-Khayal, Horst, and Pardalos (1992), Edmunds and Bard (1991), Bard (1988), and Fortuny-Amat and McCarl (1981) to the quadratic-quadratic case. Edmunds and Bard (1992) further extended the approach to an integer linear-quadratic BPP.

Both Bard and Falk (1982) and Fortuny-Amat and McCarl (1981) focused on transforming the new single-level problem to a more manageable form. More specifically, Bard and Falk (1982) provided a separable representation of the nonlinear complementary slackness constraints. The new problem is still non-convex, but all functions are separable and a BB technique was applied to find global solutions. Fortuny-Amat and McCarl (1981) introduced new binary variables and large positive numbers to linearize the complementary slackness constraints.

The new problem is a mixed integer quadratic problem. For a fixed binary variable, the new problem is convex and can be readily solved for a global optimum. A BB technique is used to enumerate the possibilities for the binary variable and solve the new problem at each iteration. Bard and Moore (1990) followed Fortuny-Amat and McCarl's method of suppressing the complementary slackness constraints first, and solved the resulting sub-problem. A check is made at each iteration to check if the complementary constraints are satisfied. If so, the corresponding point is feasible. If not, a branch and bound scheme is used to implicitly examine all possible combinations of complementary slackness. Segall (1990) used this method to solve a bi-level geometric programming problem. Bianco, Caramia, and Giordani (2009) used Fortuny-Amat and McCarl's method and solved a mixed integer linear problem after applying KKT conditions on a hazmat transportation network design problem.

There are also authors using commercial optimization solvers or heuristic algorithm to solve a linear bi-level problem (Bianco, Caramia, and Giordani 2009). For more complicated multilevel models with non-convex objective functions, global solution algorithms have to be applied in order to guarantee the global optimal solution. Sinha and Sinha (2002) applied the KKT condition twice to transfer a three-level programming problem to single level. The resulting problem is highly non-convex and nonlinear. They only found a local optimal solution using standard techniques. Wang (2002) designed a sensitivity analysis-based heuristic algorithm to solve a bi-level problem. Asgari, Farahani, and Goh (2013) used an interval branch and bound (IBB) to solve their non-convex nonlinear integer programming model for a bi-level model with one shipping company and two relay hub ports.

Finally, as pointed out by Bard and Falk (1982), a bi-level programming problem may not possess a solution when a certain player is indifferent among a number of solution points. If faced with multiple choices, there is no guarantee that the second-level player will select the value that also optimizes the first-level player’s objective function. This unstable optimal solution of bi-level programming models is also illustrated by Bianco, Caramia, and Giordani (2009).

4. MODEL CONSTRUCTION

As discussed in Chapter 1, the container shipment chain has many characteristics that are similar to a supply chain. In a supply chain, an echelon stands for the group of players at the same level of the chain. As the containers are transported from the shippers at the origin to the consignees at the destination, they pass three main segments: the ocean shipment part, ocean to land transfer, and the land shipment part. Starting from the export ports overseas, the transportation operators involved include shipping companies as the ocean carrier, terminal operators as the transfer point from ocean to land, and railway or trucking companies as the inland carriers to the final destinations. The three segments are the three levels/echelons along the shipment chain, and there is usually more than one player at one echelon. When the Panama Canal is used, the canal operator is an additional level in the shipment chain. Generally, competition and cooperation exist both within and between echelons. Each player has its own economic objective (maximizing profit) and a set of control variables.

Fan's (2008) model was targeted at minimizing the ocean carrier's total cost, which consists of vessel operating costs, railway charges, and Panama Canal charges. Jula and Leachman (2011a, b) minimized the shippers' total cost, which includes the total transportation cost and inventory cost. Both formulation types used single objective functions and incorporated the charges by other transportation operators (rail, terminal, canal, etc.) as fixed values, indicating that the authors did not consider interactions among the players. In reality, each player in the shipment chain tries to maximize individual gains by choosing an optimal strategy and responding to other players' strategies. Players may form coalitions or compete with others. Coalition members may stay in their coalition or decide to defect to another one that makes a higher tender offer. The dynamic decision-making process continues until a stable equilibrium is reached where no player may unilaterally defect to another coalition and earn a higher profit.

In this study, the interactions between transportation operators in the U.S. containerized-import transportation industry are analyzed using cooperative game theory (CGT). Section 4.1 explains how the coalition values are derived from the bi-level mathematical models and describes the structure of bi-level models for different cooperating schemes. Section 4.2 lists the basic components of the models, illustrates two examples for model construction, and describes the KKT transformation of the second example.

4.1. Bi-Level Model Formulations and Cooperation Schemes

In the global container-shipping market, the transportation operators may form various coalitions. CGT is not concerned with the detailed negotiation process and cooperation approaches, but focuses on predicting the negotiation results, including what type of coalition will form, how its members divide coalition gains, and whether the coalition is stable.

As presented in Chapter 3 (Methodology), all the existing CGT solutions utilize the characteristic functions that calculate the coalition values. In order to find a solution for the multi-player container-shipping game, a special design is made to calculate all the possible coalition values using bi-level models. The characteristic function for coalition S in an n-person game is defined as the maximum value that coalition S could guarantee its members by coordinating the strategies of its members, no matter what the other players outside the coalition do. Assuming that defensive strategies are applied, the players outside coalition S will form a coalition and cooperate to maximize their coalition's value. In that way, the market will consist of two complementary coalitions that compete with each other. When the container-shipping market is characterized by a leader-follower relationship between the OC and the other players, bi-level optimization models are used. The first-level objective function is maximizing the leading coalition's total profit while the second-level objective function is maximizing the following coalition's total profit. Thus, one bi-level model could be solved to obtain one pair of coalition values.

With n players in the game, the total number of possible coalitions is 2^n, and the total number of bi-level models needed is 2^{n-1}. When different cooperating schemes are applied, the mathematical formulation also varies, but the mathematical models all follow the same structure and are composed of the same basic model components. Therefore, instead of presenting every model thoroughly (it is also impossible without noting who the players are in the market), a list of basic notations and functions as well as two examples are presented in the next section. The complete model structure and the model list for a specific case study are given in Chapter 5.

4.2. Basic Model Components

For an ocean carrier to ship containers from I origins through J import terminals to K inland destinations, the OC's problem is to find the optimal vessel arrangement and geographic paths so that its profit is maximized, assuming the OC's charging rate and demand are both fixed. The OC's total cost comprises vessel operating costs as well as charges paid to terminal operators, inland carriers, and the Panama Canal operator if the canal is used. Depending on the distance between the port and the destination, the land carrier could be either a truck company or a railroad carrier. Assuming that those OC service providers could not invest in their infrastructure or greatly improve their service quality in the short term, their only controlled variables are the charging rates. Some of the basic notations and functions are listed in the sub-sections.

4.2.1. *Notation Set*

Indices

i: Import origins $i = 1, 2, \ldots I$

j: Container terminals $j = 1, 2, \ldots J$

k: Import destinations $k = 1, 2, \ldots K$

s: Vessel size $s = 1, 2, \ldots S$

List of Players

OC: Ocean carrier

P_j: Terminal operator $j = 1, 2, \ldots J$

$IC_{j,k}$: Inland carrier $j = 1, 2, \ldots J;\ k = 1, 2, \ldots K$

PC: Panama Canal operator

Parameters

SZ^s: Carrying capacity of vessel size *s* in Forty-foot Equivalent Unit (FEU)

$DVCS^S$: Daily vessel cost at sea for vessel size *s* (dollars)

$DVCP^S$: Daily vessel cost at port for size *s* (dollars)

TS_{ij}^s: Average transit time at sea for route *i-j* for vessel size *s* (days)

TP_j^s: Average time at terminal *j* for vessel size *s* (days)

TL_{jk}: Average transit time inland for route *j-k* per FEU (days)

CAP_j: Annual handling capacity of terminal *j* (FEU)

DMD_k: Demand of import destination *k* (FEU)

R_{ik}: OC charging rate per FEU for O-D pair *i-k* (dollars/FEU)

PRL_j: Lower bound of charging rate by terminal *j* (dollars/FEU)

$RRL_{j,k}$: Lower bound of charging rate by inland carrier *j-k* (dollars/FEU)

CRL: Lower bound of charging rate by Panama Canal (dollars/FEU)

PRU_j: Upper bound of charging rate by terminal *j* (dollars/FEU)

$RRU_{j,k}$: Upper bound of charging rate by inland carrier *j-k* (dollars/FEU)

CRU: Upper bound of charging rate by Panama Canal (dollars/FEU)

Decision Variables

v_{ij}^s: Number of size *s* vessels on route *i-j* per year

$vl_{j,k}$: Number of FEU shipments on route *j-k* per year

pr_j: Service charge per FEU by terminal *j* (dollars/FEU)

$rr_{j,k}$: Service charge per FEU by land carrier on route *j-k* (dollars/FEU)

cr: Service charge per FEU by Panama Canal (dollars/FEU)

4.2.2. List of Functions

Revenue Function of Terminal P_j

$$R_{P_j}(pr_j, v_{ij}^s) = pr_j * \sum_{s,i}(v_{ij}^s * SZ^s), j = 1, \dots, J \tag{4.1}$$

Revenue function of Inland Carrier $IC_{j,k}$

$$R_{IC_{j,k}}(rr_{j,k}, vl_{j,k}) = rr_{j,k} * vl_{j,k}, jk = 1, \dots, J * K \tag{4.2}$$

Revenue function of the Panama Canal

$$R_{pc}\left(cr, v_{ij'}^s\right) = cr * \sum_{s,i,j'}\left(v_{ij'}^s * SZ^s\right), for\ terminal\ j'\ on\ the\ East\ Coast \tag{4.3}$$

Revenue function of Ocean Carrier

$$R_{oc} = \sum_{i,k} DMD_k * R_{ik} \tag{4.4}$$

Cost function of Terminal P_j

$$C_{P_j}(v_{ij}^s) = PRL_j * \sum_{s,i}(v_{ij}^s * SZ^s), j = 1..J \tag{4.5}$$

Cost function of Inland Carrier $IC_{j,k}$

$$C_{IC_{j,k}}(v_{ij}^s) = RRL_{j,k} * vl_{j,k}, jk = 1, \dots, J * K \tag{4.6}$$

Cost function of the Panama Canal

$$C_{pc}(v_{ij}^s) = CRL * \sum_{s,i,j'} \left(v_{ij'}^s * SZ^s\right), for\ terminal\ j'\ on\ the\ East\ coast \tag{4.7}$$

Operating Cost Function of Ocean Carrier

$$C_{oc}(v_{ij}^s) = CSTS^V + CSTP^V \tag{4.8}$$

1. Total annual vessel cost at sea

$$CSTS^V = \sum_{s,i,j}\left(DVCS^S * TS_{ij}^s * v_{ij}^s\right) \tag{4.9}$$

2. Total annual vessel cost at terminal

$$CSTP^V = \sum_{s,i,j}\left(DVCP^S * TP_{ij}^s * v_{ij}^s\right) \tag{4.10}$$

Profit function of Terminal P_j

$$f_{P_j}(pr_j, v_{ij}^s) = (pr_j - PRL_j) * \sum_{s,i}\left(v_{ij}^s * SZ^s\right), j = 1, \dots, J \tag{4.11}$$

Profit function of Inland Carrier $IC_{j,k}$

$$f_{IC_{j,k}}(rr_{j,k}, vl_{j,k}) = (rr_{j,k} - RRL_{j,k}) * vl_{j,k}, jk = 1, \dots, J * K \tag{4.12}$$

Profit function of the Panama Canal

$$f_{pc}\left(cr, v_{ij'}^s\right) = (cr - CRL) * \sum_{s,i,j'}\left(v_{ij'}^s * SZ^s\right) \tag{4.13}$$

4.3. Illustration of Example Models

There are numerous possible coalitions with *n* players in the game, and it is impossible to present all of them. For illustration purposes, two examples are given in this section.

The first one is that, when the grand coalition is formed, all players act as one entity and have one common objective function of maximizing the total profit. Payments from the OC to terminal operators and land carriers become “side payments” and are determined by negotiation inside the coalition. For the grand coalition, the mathematical model will only have one level, and its objective function is as follows:

$$Max\ v = R_{oc} - C_{oc}(v_{ij}^{s}). \tag{4.14}$$

The second example (Model Example 2) assumes that the ocean carrier forms a coalition with all the terminal and inland operators, while the Panama Canal is left out as a singleton player. Thus, the first-level coalition (the leader coalition) is $\{OC, P_1, \ldots P_J, IC_{1,1} \ldots IC_{JK}\}$. The second-level coalition (the follower coalition) is $\{PC\}$. Because members in the same coalition essentially act as one player against the other coalition, the two coalitions’ values are determined by competition between them while the final payment to each individual player is determined by negotiation results inside each coalition. For simplification, the constraint set for Model Example 2 is represented by $g_m(v_{ij}^{s}, cr)$ and $h_n(v_{ij}^{s}, cr)$. (Detailed constraints will be explained in Chapter 5 for the Case Study.) The coalition value of $\{OC, P_1, \ldots P_J, IC_{1,1} \ldots IC_{J,K}\}$ is the optimal value of v_1, and the coalition value of $\{PC\}$ is the optimal value of v_2.

4.3.1. Model Example 2

$$Max\ v_1(v_{ij}^{s}, cr) = R_{oc} - C_{oc}(v_{ij}^{s}) - \sum_j C_{P_j}(v_{ij}^{s}) - \sum_{j,k} C_{IC_{j,k}}(v_{ij}^{s}) - C_{pc}(v_{ij}^{s}) - f_{pc}(cr) \tag{4.15}$$

Subject to

$$Max\ v_2(cr, v_{ij}^{s}) = f_{pc}(cr, v_{ij}^{s}) \tag{4.16}$$

Subject to

$$g_m(v_{ij}^{s}, cr) \leq 0, m = 1, \ldots M \tag{4.17}$$

$$h_n(v_{ij}^{s}, cr) = 0, n = 1, \ldots N \tag{4.18}$$

4.4. KKT Transformation of the Bi-Level Model

The Stackelberg game is solved by first applying the Karush-Kuhn-Tucker (KKT) conditions to the second level of the mathematical models so that the bi-level model is converted to a single-level model. The new model is non-convex, and the global optimum may not be found using local optimum solutions. Using the Model Example 2, the process is illustrated as follows.

4.4.1. Original Model Example Model 2

$$Max\ v_1(v_{ij}^s, cr) \tag{4.19}$$

Subject to

$$Max\ v_2(v_{ij}^s, cr) \tag{4.20}$$

Subject to

$$g_m\left(v_{ij}^s, cr\right) \leq 0,\ m = 1, \dots, M \tag{4.21}$$

$$h_n\left(v_{ij}^s, cr\right) = 0,\ n = 1, \dots, N \tag{4.22}$$

4.4.2. Transfer the Second level by KKT

$$Max\ v_1\left(v_{ij}^s, cr\right) \tag{4.23}$$

Subject to

$$\nabla_{cr} v_2(v_{ij}^s, cr) + \sum_{m \in Active} u_m * \nabla_{cr} g_m\left(v_{ij}^s, cr\right) + \sum_{n=1}^{p} v_n * \nabla_{cr} h_n\left(v_{ij}^s, cr\right) = 0 \tag{4.24}$$

$$g_m\left(v_{ij}^s, cr\right) \leq 0,\ m = 1, \dots, M \tag{4.25}$$

$$h_n\left(v_{ij}^s, cr\right) = 0,\ n = 1, \dots, N \tag{4.26}$$

$$u_m * g_m\left(v_{ij}^s, cr\right) = 0,\ m = 1, \dots, M \tag{4.27}$$

$$u_m \geq 0,\ m = 1, \dots, M \tag{4.28}$$

5. CASE STUDY

As shown in the previous chapter, the complexity of the mathematical problem arises exponentially with the number of players. This chapter creates a case study with one ocean carrier, two terminals, one rail operator, and one Panama Canal operator. Section 5.1 explains how the case study is established, presents Model 1 for one coalition type, and shows how Model 1 is transformed to a single-level model. The list of all 32 coalitions and their according models are inserted as Appendix B. Section 5.2 discusses the sources and estimates for parameter values. Model results and sensitivity analysis are presented in the next chapter.

5.1. Coalitions and Models

The five players in the case study are: one ocean carrier (OC), one terminal operator at the Los Angles Port (P1), one terminal operator at the Norfolk Port (P2), one rail operator (R), and one Panama Canal operator (PC). The port of Hong Kong is used as the origin, and Norfolk, VA, is assumed as the destination. The OC has two route choices: the West Coast route (WCR), which involves P1 and the railroad connection (R) from P1 to final destination; and the East Coast route (ECR), which bypasses Norfolk Port and the Panama Canal. The destination is chosen to be very near P2 so that no additional inland carrier is included for the ECR. Trucking service is only used for the final door-delivery for both routes, and therefore, is not considered in the game.

Because the maximum vessel size that could be handled by the Panama Canal currently is 4,400 TEUs, the vessel operating cost for the ECR is first calculated based on 4,000-TEU vessels' normal operations, while a standard 8,000-TEU vessel is assumed for the WCR. The Panama Canal expansion is expected to be accomplished by August 2014, and the new locks will be able to handle vessels up to 13,000 TEU in capacity. By then, it is also expected both ports could serve larger vessels like PostPanama container ships. For the case study, instead of using variables for the number of different vessels, the variables for the shipment volume in FEU (feu_j for port *j*) are used. And the number of vessels calling at terminal j can be represented by feu_j/SZ^s. Note fractional vessel numbers are accepted for this case study because, in reality, only a portion of the containers carried by a vessel are for one destination.

The total number of coalitions is 32 (2^5) with five players in the game. To get the characteristic functions and values of the 32 coalitions, 16 bi-level models are needed. The first level of the bi-level model is for the leader coalition of OC and any of its partners, while the second level is for the follower coalition of all the other players. Each bi-level model has a pair of unique objective functions and a set of constraints, but all the models' structures are similar and could be represented by the same list of notations and functions. The 16 models and their constraint sets are listed in Appendix A. For the 16 models, the i^{th} model is recorded as M_i. And v_i^1 and v_i^2 are used to represent the 1st-level and 2nd-level objective functions of M_i, respectively.

In the following sub-sections, one type of the cooperation schemes (coalition {OC, P1} against coalition {P2, PC, R}) is used to illustrate how a bi-level model (Model 1) should be constructed for it and how Model 1 is transferred to one level using KKT conditions. Notations from Chapter 3 and 4 will be continually used.

5.1.1. Model 1 Illustration

$$Max\ v_1^1 = R_{oc} - C_{oc} - C_{p1} - R_{p2} - R_{pc} - R_r = \sum_j R_j * feu_j - \sum_{j,s}\left(DVCS^s * TS_j^s * \frac{feu_j}{SZ^s}\right) - \sum_j\left(DVCP^s * TP_j^s * \frac{feu_j}{SZ^s}\right) - PRL_1 * feu_1 - pr_2 * feu_2 - cr * feu_2 - rr * feu_1 \tag{5.1}$$

Subject to

$$\sum_j \left(feu_j\right) \geq DMD \tag{5.2}$$

$$feu_j \leq Cap(j), \forall j \tag{5.3}$$

$$feu_j \geq 0, \forall j \tag{5.4}$$

$$Max\ v_1^2 = f_{p2} + f_{pc} + f_r = (pr_2 - PRL_2) * feu_2 - (cr - CRL) * feu_2 - (rr - RRL) * feu_1 \tag{5.5}$$

Subject to

$$PRL_2 \leq pr_2 \leq PRU_2 \tag{5.6}$$

$$RRL \leq rr \leq RRU \tag{5.7}$$

$$CRL \leq cr \leq CRU \tag{5.8}$$

Equation 5.1 is total profit function of the coalition {OC, P1}, which is a function of OC's revenue minus total vessel operating cost, container handling cost at P1, and OC's payments to P2, PC, and railroad. Equations 5.2 to 5.3 are demand and capacity constraints. Equation 5.5 is the 2nd-level objective function—the total profit function of coalition {P2, PC, R}. It is a function of rates and shipment volume. The constraints at the second level set the upper and lower bounds for the rate variables. The Lagrangian function of the 2nd-level problem is given as below.

$$L(pr_2, cr, rr) = (pr_2 - PRL_2)feu_2 - (cr - CRL)feu_2 - (rr - RRL)feu_1 + u_1(pr_2 - PRL_2 - s_1^2) + u_2(PRU_2 - pr_2 - s_2^2) + u_3(rr - RRL - s_3^2) + u_4(RRU - rr - s_4^2) + u_5(cr - CRL - s_5^2) + u_6(CRU - cr - s_6^2) \tag{5.9}$$

Using the Karush-Kuhn-Tucker (KKT) transformation, the new single-level model is shown by Equations 5.10 to 5.21.

$$Max\ v_1^1 = R_{oc} - C_{oc} - C_{p1} - R_{p2} - R_{pc} - R_r = (\sum_j R_j) * feu_j - \sum_j \left(DVCS^s \times TS_j^s \times \frac{feu_j}{SZ^s}\right) - \sum_j \left(DVCP^s * TP_j^s * \frac{teu_j}{SZ^s}\right) - PRL_1 * feu_1 - pr_2 * feu_2 - cr * feu_2 - rr * feu_1$$

(5.10)

Subject to

$$\sum_j (\mathrm{feu_j}) \geq \mathrm{DMD} \tag{5.11}$$

$$\mathrm{feu_j} \leq \mathrm{Cap(j)}, \forall \mathrm{j} \tag{5.12}$$

$$\mathrm{feu_j} \geq 0, \forall \mathrm{j} \tag{5.13}$$

$$\mathrm{PRL_2} \leq \mathrm{pr_2} \leq \mathrm{PRU_2} \tag{5.14}$$

$$\mathrm{RRL} \leq \mathrm{rr} \leq \mathrm{RRU} \tag{5.15}$$

$$\mathrm{CRL} \leq \mathrm{cr} \leq \mathrm{CRU} \tag{5.16}$$

$$\nabla \mathrm{f(x^*)} + \sum_{\mathrm{i \in Active}} \mathrm{u_i} \nabla \mathrm{g_i(x^*)} = 0 \tag{5.17}$$

$$\mathrm{g_i(x^*)} - \mathrm{s_i^2} = 0, \mathrm{i} = 1, 2, \ldots, 6 \tag{5.18}$$

$$\mathrm{u_i g_i(x^*)} = 0, \mathrm{i} = 1,2, \ldots, 6 \tag{5.19}$$

$$\mathrm{s_i^2} \geq 0, \mathrm{i} = 1,2, \ldots 6 \tag{5.20}$$

$$\mathrm{u_i} \geq 0, \mathrm{i} = 1,2, \ldots 6 \tag{5.21}$$

5.1.2. Model Solution and Shapley Value Calculation

After KKT transformation, the new single-level model has a set of complementary slackness constraints, and also has a nonlinear non-convex objective function. Usually, a global optimization algorithm is needed to guarantee a real optimal solution. For this model, however, the optimal rates could be easily found by solving the constraint sets first. The objective function thus becomes a linear function with only shipment volume variables, and the problem becomes a linear programming problem, whose global optimal solution equals the local solution. SAS 9.3 is applied to solve all 16 models. Based on Equation 3.8, each player's Shapley value calculation is presented in Equation 5.22 to Equation 5.26.

Terminal 1's Shapley Value:

$$\emptyset_{\mathrm{P1}} = \frac{4!0!}{5!}(v_{15}^{1} - v_{14}^{1}) + \frac{3!1!}{5!}(v_{13}^{1} - v_{10}^{1}) + \frac{3!1!}{5!}(v_{12}^{1} - v_{9}^{1}) + \frac{3!1!}{5!}(v_{11}^{1} - v_{8}^{1}) + \frac{3!1!}{5!}(v_{0}^{2} - v_{1}^{2}) + \frac{2!2!}{5!}(v_{7}^{1} - v_{4}^{1}) + \frac{2!2!}{5!}(v_{6}^{1} - v_{3}^{1}) + \frac{2!2!}{5!}(v_{5}^{1} - v_{2}^{1}) + \frac{2!2!}{5!}(v_{4}^{2} - v_{7}^{2}) + \frac{2!2!}{5!}(v_{3}^{2} - v_{6}^{2}) + \frac{2!2!}{5!}(v_{2}^{2} - v_{5}^{2}) + \frac{3!1!}{5!}(v_{1}^{1} - v_{0}^{1}) + \frac{3!1!}{5!}(v_{8}^{2} - v_{11}^{2}) + \frac{3!1!}{5!}(v_{9}^{2} - v_{12}^{2}) + \frac{3!1!}{5!}(v_{10}^{2} - v_{13}^{2}) + \frac{4!}{5!}(v_{14}^{2} - v_{15}^{2}) \quad (5.22)$$

Terminal 2's Shapley Value:

$$\emptyset_{\mathrm{P2}} = \frac{4!0!}{5!}(v_{15}^{1} - v_{13}^{1}) + \frac{3!1!}{5!}(v_{14}^{1} - v_{10}^{1}) + \frac{3!1!}{5!}(v_{12}^{1} - v_{7}^{1}) + \frac{3!1!}{5!}(v_{11}^{1} - v_{6}^{1}) + \frac{3!1!}{5!}(v_{0}^{2} - v_{2}^{2}) + \frac{2!2!}{5!}(v_{9}^{1} - v_{4}^{1}) + \frac{2!2!}{5!}(v_{8}^{1} - v_{3}^{1}) + \frac{2!2!}{5!}(v_{5}^{1} - v_{1}^{1}) + \frac{2!2!}{5!}(v_{4}^{2} - v_{9}^{2}) + \frac{2!2!}{5!}(v_{3}^{2} - v_{8}^{2}) + \frac{2!2!}{5!}(v_{1}^{2} - v_{5}^{2}) + \frac{3!1!}{5!}(v_{2}^{1} - v_{0}^{1}) + \frac{3!1!}{5!}(v_{6}^{2} - v_{11}^{2}) + \frac{3!1!}{5!}(v_{7}^{2} - v_{12}^{2}) + \frac{3!1!}{5!}(v_{10}^{2} - v_{14}^{2}) + \frac{4!}{5!}(v_{13}^{2} - v_{15}^{2}) \quad (5.23)$$

Panama Canal's Shapley value:

$$\emptyset_{\mathrm{PC}} = \frac{4!0!}{5!}(v_{15}^{1} - v_{12}^{1}) + \frac{3!1!}{5!}(v_{14}^{1} - v_{9}^{1}) + \frac{3!1!}{5!}(v_{13}^{1} - v_{7}^{1}) + \frac{3!1!}{5!}(v_{11}^{1} - v_{5}^{1}) + \frac{3!1!}{5!}(v_{0}^{2} - v_{3}^{2}) + \frac{2!2!}{5!}(v_{10}^{1} - v_{4}^{1}) + \frac{2!2!}{5!}(v_{8}^{1} - v_{2}^{1}) + \frac{2!2!}{5!}(v_{6}^{1} - v_{1}^{1}) + \frac{2!2!}{5!}(v_{4}^{2} - v_{10}^{2}) + \frac{2!2!}{5!}(v_{2}^{2} - v_{8}^{2}) + \frac{2!2!}{5!}(v_{1}^{2} - v_{6}^{2}) + \frac{3!1!}{5!}(v_{3}^{1} - v_{0}^{1}) + \frac{3!1!}{5!}(v_{5}^{2} - v_{11}^{2}) + \frac{3!1!}{5!}(v_{7}^{2} - v_{13}^{2}) + \frac{3!1!}{5!}(v_{9}^{2} - v_{14}^{2}) + \frac{4!}{5!}(v_{12}^{2} - v_{15}^{2}) \quad (5.24)$$

Railway's Shapley value:

$$\emptyset_{\mathrm{R}} = \frac{4!0!}{5!}(v_{15}^1 - v_{11}^1) + \frac{3!1!}{5!}(v_{14}^1 - v_8^1) + \frac{3!1!}{5!}(v_{13}^1 - v_6^1) + \frac{3!1!}{5!}(v_{12}^1 - v_5^1) + \frac{3!1!}{5!}(v_0^2 - v_4^2) + \frac{2!2!}{5!}(v_{10}^1 - v_3^1) + \frac{2!2!}{5!}(v_9^1 - v_2^1) + \frac{2!2!}{5!}(v_7^1 - v_1^1) + \frac{2!2!}{5!}(v_3^2 - v_{10}^2) + \frac{2!2!}{5!}(v_2^2 - v_9^2) + \frac{2!2!}{5!}(v_1^2 - v_7^2) + \frac{3!1!}{5!}(v_4^1 - v_0^1) + \frac{3!1!}{5!}(v_5^2 - v_{12}^2) + \frac{3!1!}{5!}(v_6^2 - v_{13}^2) + \frac{3!1!}{5!}(v_8^2 - v_{14}^2) + \frac{4!}{5!}(v_{11}^2 - v_{15}^2) \tag{5.25}$$

Ocean carrier's Shapley value:

$$\emptyset_{\mathrm{OC}} = \frac{4!0!}{5!}(v_{15}^1 - v_0^2) + \frac{3!1!}{5!}(v_{14}^1 - v_1^2) + \frac{3!1!}{5!}(v_{13}^1 - v_2^2) + \frac{3!1!}{5!}(v_{12}^1 - v_3^2) + \frac{3!1!}{5!}(v_{11}^1 - v_4^2) + \frac{2!2!}{5!}(v_{10}^1 - v_5^2) + \frac{2!2!}{5!}(v_9^1 - v_6^2) + \frac{2!2!}{5!}(v_8^1 - v_7^2) + \frac{2!2!}{5!}(v_7^1 - v_8^2) + \frac{2!2!}{5!}(v_6^1 - v_9^2) + \frac{2!2!}{5!}(v_5^1 - v_{10}^2) + \frac{3!1!}{5!}(v_4^1 - v_{11}^2) + \frac{3!1!}{5!}(v_3^1 - v_{12}^2) + \frac{3!1!}{5!}(v_2^1 - v_{13}^2) + \frac{3!1!}{5!}(v_1^1 - v_{14}^2) + \frac{4!}{5!}(v_0^1 - v_{15}^2) \tag{5.26}$$

5.2. Parameter Estimates

5.2.1. Daily Vessel Operating Cost

Vessel operating cost is a function of shipping speed, fuel consumption rate, and other variable costs, including fuel, crew, maintenance, and administration costs. The Army Corps of Engineers Aggregated Vessel Operating Cost Model (AVOCM) has input values regarding ship size, speed, fuel usage rate, and average opportunity cost of capital, as well as other endogenized costs like insurance and operating cost (Army Corps of Engineers 2007). Fan (2010) used daily charter rates to replace AVCOM's fixed capital asset and operating costs and derived the estimation functions for the daily vessel operating cost (Equations 6.27 and 6.28). This study re-estimates the vessel operating costs using updated fuel prices and daily hire rates from the Bloomberg Professional Service database (Bloomberg L. P. 2013a, b).

$$DVCS_s = AU_s * MDO + EC_s * HVO + DHirerate_s \tag{5.27}$$

$$DVCP_s = AU_s * MDO + DHirerate_s \tag{5.28}$$

$DVCS_s$: Daily vessel cost at sea for container vessel of size *s* (dollars)

$DVCP_s$: Daily vessel cost at port for container vessel of size *s* (dollars)

AU_s: Bunkerage consumption rate for auxiliary power generation for container vessel of size *s* (metric tons/day)

EC_s: Bunkerage consumption rate for propulsion mover(s) for container vessel of size *s* at economic speed (metric tons/day)

MDO: Marine diesel oil price (dollars/metric ton)

HVO: Heavy viscosity oil price (dollars/metric ton)

$DHirerate_s$: Daily charter rate of container vessel of size *s* (dollars/day)

The values of economic speed and engine fuel consumption rates for different container ship sizes are available from AVOCM. Only 4,000-TEU and 8,000-TEU vessels are used in the case study (Table 5.1). Fuel prices fluctuate vastly through time. Figure 5.1 shows the HVO and MDO price changes from April 2010 to March 2013. The average price from 2010 to 2012 based on the Los Angeles price (Bloomberg L. P. 2013a) is used: $917 per metric ton for MDO and $603 per metric ton for HVO (380 centistokes).

Table 5.1. Fuel Consumption Rates and Economic Speeds of the Vessels

Vessel Category	Vessel size (TEU)	AU (MT/Day)	EC (MT/Day)	Economic Speed (NM/Hour)
Panamax	4,000	3.9	103.2	21.3
PostPanamax	8,000	5.2	202.6	25

Figure 5.1. HVO and MDO Price Changes

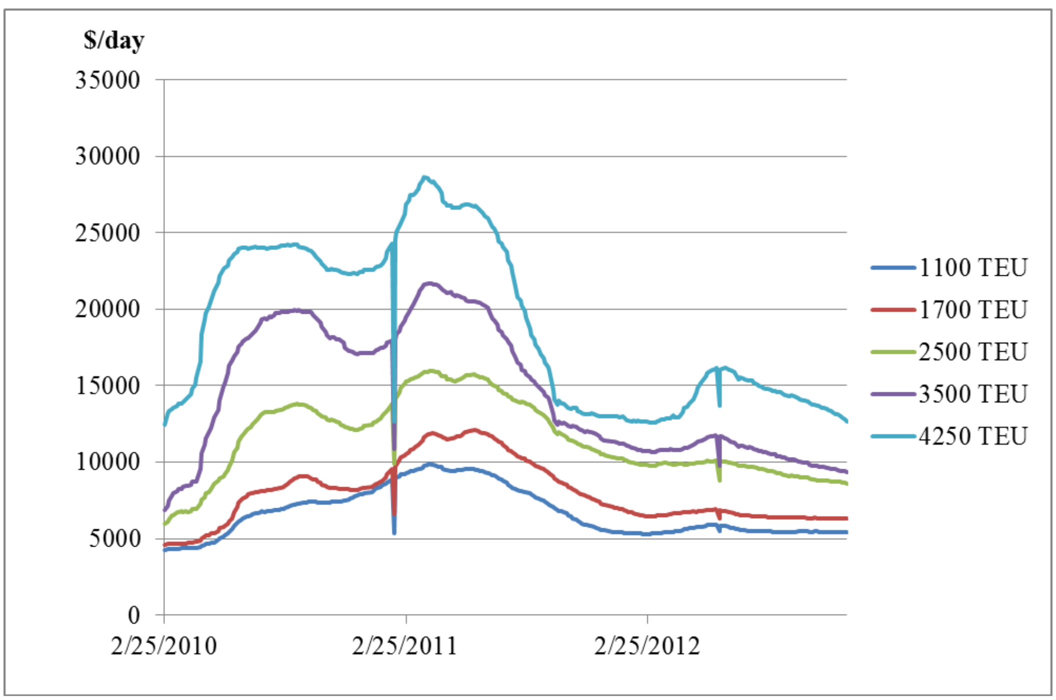

Figure 5.2. Daily Hire Rates Changes

The daily hire rate changes for vessel sizes of 11,100 TEU, 1,700 TEU, 2,500 TEU, 3,500 TEU, and 4,250 TEU from 2010 to 2012 are shown in Figure 5.2 (Bloomberg L. P. 2013a).

The average values from 2010 to 2012 are used to estimate a regression function of daily hire rates on vessel size *s* (Equation 6.29). The estimated values of *a* and *b* are 30 and 0.7672. The estimation R^2 is 0.97 (Figure 5.3). The daily hire rates for the vessels for different vessel sizes are predicted using the regression function. Daily hire rate is estimated as $16,820 for a 4,000-TEU vessel and $28,627 for an 8,000-TEU vessel.

$$DHirerate_s = a * s^b \tag{5.29}$$

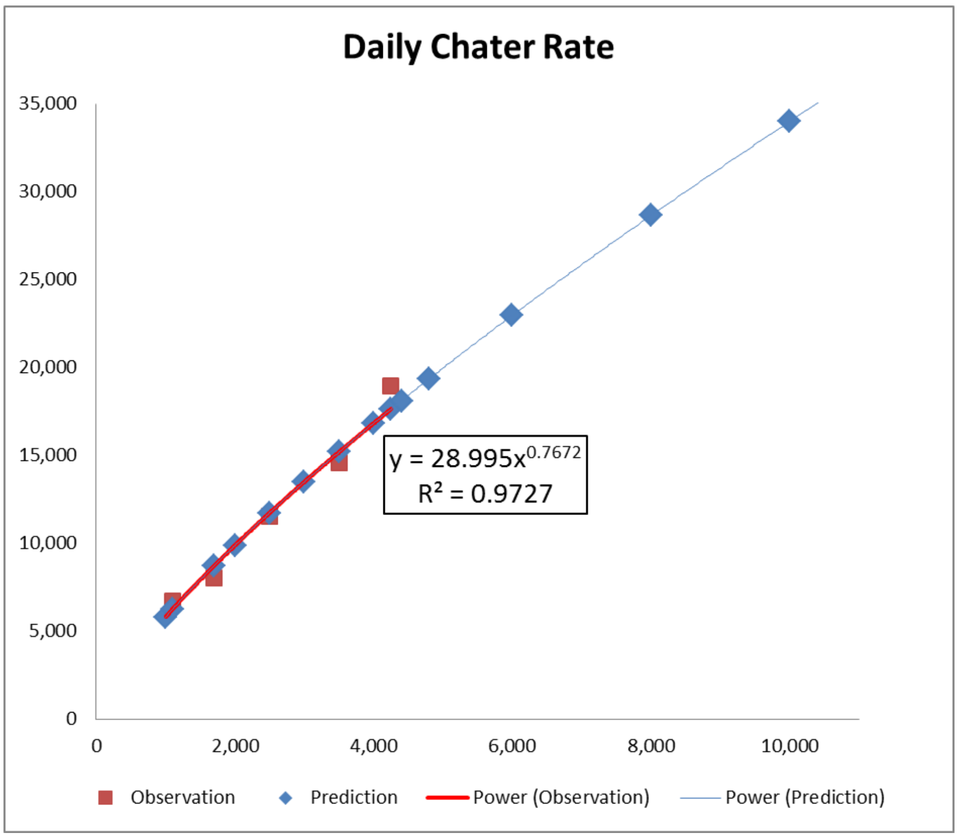

Figure 5.3. Daily Hire Rates Estimation

5.2.2. Transit Time Estimates

Container terminals usually operate approximately 28 to 35 moves per crane per hour at top North American ports (Le-Griffin and Murphy 2006). Container productivity is critical for container ports like LA and NF. Thus, it is assumed both terminals in the case have the capacity to efficiently handle the PostPanama vessels, and there will be no difference between the two ports' vessel handling time. With three cranes with 35 moves per crane per hour serving a vessel with a capacity of 8,000 TEU and a loading factor of 0.8, it takes about 2.5 days to off-load the vessel. With two cranes with 30 moves per crane per hour serving a vessel with capacity of 4,000 TEU and loading factor of 0.8, it takes about 2.2 days. Considering other activities (paperwork, waiting, supply, etc.) that further cost more time, the total port time is estimated as three days for the PostPanamax vessel (8,000 TEU) and 2.5 days for the Panamax vessel (4,000 TEU).

Additional days are needed when the Panama Canal is used for the ECR. The Canal uses two quality service-level indicators: 1) average waiting time to transit the Canal; and 2) average transit time. Their combination is called Canal Waters Time (CWT) (Panama Canal Authority 2006). On average, the transit time takes eight to 10 hours to go through the Canal (Panama Canal Authority 2010). The waiting time could vary depending on the congestion condition and whether a transit is reserved beforehand. Typically, the reserved CWT is about 17 hours (0.7 days) versus 36 hours (1.5 days) for non-reserved (Wilson, Dahl, and Fan 2010). For the ECR, 1.5 days are added to port time. The time at sea is calculated using economic speeds from the AVOCM model for each vessel size (Army Corps of Engineers 2007). Table 5.2 lists the economic speed, port distance overseas, traveling time at sea, and time at port used in the case study.

Table 5.2. Vessel Time Estimates

	Economic Speed (nautical miles/hour)	Sea Distance (nautical miles)	Time at Sea (days)	Time at Port (days)
LA 8,000 TEU	25	7,455	10.6	3
NF 8,000 TEU	25	12,883	18.4	4.5
NF 4,000 TEU	21.3	12,883	21.6	4

Sources: Data from Fan (2010) and Army Corps of Engineers (2007).

The railway shipment time from LA to Norfolk, VA, is calculated from two segments: LA to Chicago and Chicago to Norfolk. Based on the two segments' estimated shipment time (Table 5.3), the total inland container transit time is estimated to be four days for LA to Norfolk, VA. The transit time from Norfolk to VA is assumed to be 0.5 days. It is assumed that cooperation between any transportation operator (the terminal, the Panama Canal, or the railroad) and the OC will save the OC half a day of normal transit time.

Table 5.3. Container Inland Time Estimates for WCR

	Railway Company	Mileage	Speed (mph)	Days
LA to Chicago	BNSF	2,161	36	2.5
Chicago to Norfolk, VA	CSX	964	30	1.34

Source: Data from Fan (2010).

5.2.3. *Inventory Cost*

Other than transportation cost paid directly to carriers, another major cost sector for shippers is the opportunity cost of working capital tied up in the inventory throughout the supply chain. Although it is assumed that the OC chooses the optimal routes to maximize its profit and that inventory costs are not directly reflected in the OC's profit function, the difference of the transit time has implicit impact on the OC's route choice. To reflect shippers' perceptions of shipping speed, different charging rates of the OC are assumed. The OC's charging rate R_1 for a quicker route (WCR in this case) is set to be higher than R_2 for the slower ECR. The reason is that quicker delivery saves shippers inventory cost. To estimate the difference between the two rates, Equation 6.30 is derived based on Wardrop's First Principle. At equilibrium, both routes should have equalized lowest cost for the shippers. I_{rt} is the inventory cost for route rt (rt = 1 or 2).

$$R_1 + I_1 = R_2 + I_2 \tag{5.30}$$

There are three types of inventories in a supply chain: cycle inventory, safety stock, and pipeline inventory. Cycle inventory is a function of the replenishment frequency and is independent of the selection of the route, and therefore is irrelevant for route choices. Safety stock is the extra inventory kept to satisfy the customer demand on time. It is a function of the customer service level, the uncertainties in the shipment lead time, and the demand forecast error (Jula and Leachman 2011a). Assuming demand is deterministic and there is no shipment uncertainty, safety stock is not considered as well. Pipeline inventory is the amount of inventory in transit. The annual inventory cost per unit is a function of the transportation time and daily unit pipeline inventory cost (DPC) (Equation 6.31). DPC is calculated as an inventory carrying rate (annual interest rate for commercial loans) times the amount of capital invested per unit of inventory (Equation 6.32).

$$I_{rt} = DPC * T_{rt} \tag{5.31}$$

$$DPC = r * UV/365 \tag{5.32}$$

I_{rt}: Total annual pipeline inventory cost per FEU for route *rt* (dollars)

DPC: Daily pipeline inventory cost per FEU (dollars)

T_{rt}: Transit time per FEU for route *rt* (days)

r: Annual interest rate

UV: Average cargo value per FEU (dollars)

Jula and Leachman (2011b) suggest a 20% inventory carrying rate per year for replenishment of goods with long-term demand, and 50% if retail prices are declining with time or if the products experience rapid obsolescence. An average inventory carrying rate of 35% is assumed for simplicity. Using joint data from PIERS database, World Trade Atlas (WTA) database, and Pacific Maritime Association's database, Leachman (2010) calculated the average declared values per cubic foot for containerized imports from Asia to different coast ports in the United States (Table 5.4). The average cargo value per FEU (UV) is estimated assuming the average usable space is about 2,684 cubic feet for a high-cube 40-foot container (9.5-foot high and 40-foot long). Using Equation 6.32, daily pipeline inventory cost (DPC) is estimated in Table 5.4. Using daily pipeline inventory cost of $56.00 per day and Equation 6.30, the charging rate difference between the two routes is calculated as $R_1 - R_2 = I_2 - I_1 = 56(T_2 - T_1)$.

Table 5.4. Daily Pipeline Inventory Cost Calculation

	Asia to U.S.	Asia to West Coast	Asia to East/Gulf Coast
Cargo Value ($/cu ft)	21.66	22.66	18.57
UV ($/FEU)	58,135.44	60,819.44	49,841.88
DPC ($/FEU/Day)	55.75	58.32	47.79

Source: Compiled using data from Leachman (2010).

5.2.4. Transportation Rates

Shipping rates, terminal charges, canal tolls, and railway rates are all sensitive information and very volatile through time. Spot market rates from public sources are obtained to estimate general ranges.

5.2.4.1. Trans-Pacific shipping rates

On August 16, 2013, according to SCFI data issued by the Shanghai Shipping Exchange, the spot rate from Shanghai to the U.S. West Coast was $1,941 per FEU, 27.7% below the level in the same week last year and 12.6%, or $280, less than at the beginning of 2013. The spot rate to the U.S. East Coast was $3,408 in the week ending August 16, 13.6% down from the same week in 2012, but up 1.5%, or $50, from January 1 (Journal of Commerce 2013c). For the case study, the shipping rate R_1 charged by the OC for the all-water route (WCR) is assumed to be $3,400 per FEU. Depending on the vessel size used for ECR, the transit time and inventory cost differences between the two routes will be different. Using Equations 6.30, 6.31, and 6.32, the shipping rate R_2 for the transcontinental route (ECR) could be derived accordingly.

5.2.4.2. Railroad charging rates

The rail rate ranges are estimated based on the most current Public Use Waybill File (U.S. Surface Transportation Board 2011), which contains sample data on rail shipments from origin Business Economic Area (BEA) to termination BEA. Because there is no railroad company with direct shipment from Los Angeles to Norfolk on its own network, the rail route is analyzed based on the LA-Chicago segment (operated by BNSF) and the Chicago-Norfolk, VA, segment (operated by CSX). The line haul rates per container are calculated using "Expanded Freight Revenue" divided by "Expanded Trailer/Container Count" for shipments from LA (BEA = 160) to Chicago (BEA = 64), and for shipments from Chicago to Norfolk, VA (BEA = 20). Only containerized cargoes (STCC2 = "46") are counted. The calculated rates are summarized in Table 5.5.

Using the lowest record as the lower bound of railroad rates and the 90% percentile value as the upper bound, the railroad rate for LA to Norfolk, VA, is estimated to range from $1,420 to $3,400 per container. As the railway does not report the size of the containers, it is assumed the majority of those are 53-foot domestic containers.

According to spot market reports, the west-to-east door-to-door spot rates in early May 2013 were about $2,300 for a 53-foot intermodal container, and the spot rate for Los Angeles-New Jersey fell 2.4% ($80) to $3,285 in the second week of May (Journal of Commerce 2013d). In early August, the west to east bound rate rose again to about $2,390. The largest increase in the first week of August was the Los Angeles-Atlanta route: 2.4% ($70) to $3,000 (Journal of Commerce 2013b). Comparing the two sources, the lower and upper bound estimates for the railroad rates are reasonable for this study.

Table 5.5. Railway Shipment Rates Summary

Quantile	LA-Chicago Rate	Chicago-NF Rate
100% Max	3670	2751
99%	2187	1835
95%	1997	1584
90%	1887	1511
75% Q3	1692	1388
50% Median	1435	1163
25% Q1	1184	1043
10%	1007	957
5%	870	901
1%	756	843
0% Min	665	756

The rates are transferred from 35-foot containers to high-cube 40-foot containers based on the usage capacity ratios. Usable capacity for a domestic container (a 35-foot-long container) is about 4,000 cubic feet and 2,684 cubic feet for a high-cube 40-foot container . Therefore, the final upper and lower bounds for railroad rates for ECR are estimated as $953 per FEU and $2,280 per FEU, respectively.

5.2.4.3. Port and Panama Canal charging rates

The average terminal handling cost for some European countries could be found through the APL website (www.APL.com). Those rates range from $127 to $300 per container. Based on personal communication with Chuck Raymond (former CEO of Horizon Lines, Inc.) and David Smith (CEO of Work Cat Engineering LLC), the lowest expected container handling rate at some terminals of the Norfolk port is about $150 per container. Assuming there is no big difference between the two ports’ costs and charging rates, the lower and upper bounds of the terminal charges for the case study are set as $150 and $300, respectively.

Compared with the other rates, the Panama Canal tolls are relatively easy to estimate. The canal tolls were $54/TEU in 2007 and $72/TEU in 2009 and 2010. Including ancillary fees, the total fee in 2010 is about $88/TEU if booking service is used, while about $80/TEU without booking beforehand (Wilson, Dahl, and Fan 2010). The CEO of Maersk Line said the fees for ships to go through the Panama Canal have tripled in the past five years to $450,000 per passage for a vessel carrying 4,500 containers since 2009 (Park 2013). That is about $100/TEU if all the containers are 20 feet. The lower bound of the Panama Canal rate is set as $160/FEU, and the upper bound is set as $220/FEU.

6. RESULT ANALYSIS

6.1. Model Results and CGT Solutions

As stated in Chapter 5, the container vessel used for the East Coast route (ECR) is 4,000 TEU before the Panama Canal expansion is finished and 8,000 TEU after the expansion. The West Coast route (WCR) is served by 8,000-TEU vessels both before and after the expansion. For all ships, 80% carry capacity is assumed. The total containerized demand at the destination (Norfolk, VA) is assumed to be 64,000 FEU annually, and is shared by the two routes. To analyze the impact of capacity constraints, the models are both calculated with assumptions that there are no terminal TEU capacity constraints, and with assumptions that both terminals could only handle 80% of total container demand. Hence, in all, four scenarios are compared.

Scenario 1 (S1): "Base Case: Before Canal Expansion & No Capacity Constraints."

Scenario 2 (S2): "After Canal Expansion & No Capacity Constraints."

Scenario 3 (S3): "Before Canal Expansion & Capacity Constraints at Terminals."

Scenario 4 (S4): "After Canal Expansion & Capacity Constraints at Terminals."

The models' results are in Appendix B Table B1, Table B2, Table B3, and Table B4. As Model 15's result shows, if the grand coalition is formed, the OC prefers the WCR before the Canal expansion is finished. However, after the expansion is finished and both routes are served by the 8,000-TEU vessel, the OC chooses ECR via the Panama Canal because of a higher profit.

The Shapley values are presented in Table 6.1. In order to compare scenarios, the ratios of the Shapley Value are also calculated in each scenario and listed in Table 6.1. The ratios are a reflection of players' relative market powers under each scenario. A player's Shapley value is the total profit allocation for that player because the models' objective functions are profit maximization. The values are all divided by 64,000 for the purpose of easy presentation and interpretation. In that way, the Shapley value could be directly interpreted as a unit profit per FEU because the total shipment volume is 64,000 FEU, except for the players in S3 and S4. Under the capacity constraint assumption in S3 and S4, both routes handle part of the total shipment volume by the OC. So to get the real profit per FEU for those players in S3 and S4, the Shapley value has to be multiplied by 64,000 and divided by the number of real container volume handled by that player. The translated unit profit per FEU values are presented in Table 6.2.

Table 6.1. Shapley Values and Value Ratios in S1, S2, S3, S4

	P1	P2	R	PC	OC	Total
S1	56.62	62.33	75.50	35.56	1807.68	2037.69
S2	0.00	152.60	0.00	72.14	1955.26	2180.00
S3	80.82	63.94	337.22	31.82	1589.57	2103.37
S4	30.53	122.08	265.40	57.71	1645.61	2121.34
S1 Ratio	0.03	0.03	0.04	0.02	0.89	1.00
S2 Ratio	0.00	0.07	0.00	0.03	0.90	1.00
S3 Ratio	0.04	0.03	0.16	0.01	0.75	1.00
S4 Ratio	0.01	0.06	0.13	0.03	0.78	1.00

Table 6.2. Unit Profit Values in S1, S2, S3, S4

	P1	P2	R	PC	OC
S1	56.62	62.33	75.50	35.56	1807.68
S2	0.00	152.60	0.00	72.14	1955.26
S3	101.03	319.71	414.24	159.09	1589.57
S4	152.66	152.60	1327.00	72.14	1645.61

Using Theorem 1 to test if the Shapley Values are in the core, the total payment to the members in every possible coalition $S \subset N$ is compared with *v(S)*. All four sets of Shapley values are tested in Tables 6.3 to 6.6 with the values of $\sum_{i \in S} y_i$ (sum of Shapley Values), v(S), and their differences listed. If some of the differences between $\sum_{i \in S} y_i$ and v(S) are negative (the last column), the Shapley Value is not in the core. For a solution not in the core, the solution may not be fully accepted by the players; and some players may defect to other coalitions that offer them better profits. But the Shapley value still works as a measure of relative market power of the players, since it measures the average attribution made by each player. As Tables 6.3 to Table 6.6 show, both S1 and S3's Shapley values are not in the core.

Table 6.3. Coalition Values for S1

players	v(S)	OC	P1	P2	PC	R	sum(yi)	sum(yi) - v(S)
OC	1716.25	1807.68					1807.68	91.43
OC P1	1716.25	1807.68	56.62				1864.30	148.05
OC P2	1872.50	1807.68		62.33			1870.01	-2.49
OC PC	1801.88	1807.68			35.56		1843.24	41.37
OC R	1882.38	1807.68				75.50	1883.18	0.80
OC P1 P2	1872.50	1807.68	56.62	62.33			1926.63	54.13
OC P1 Pc	1801.88	1807.68	56.62		35.56		1899.86	97.99
OC P1 R	2037.69	1807.68	56.62			75.50	1939.80	-97.89
OC P2 PC	1958.13	1807.68		62.33	35.56		1905.57	-52.55
OC P2 R	1882.38	1807.68		62.33		75.50	1945.51	63.13
OC PC R	1882.38	1807.68			35.56	75.50	1918.74	36.36
OC P1 P2 PC	1958.13	1807.68	56.62	62.33	35.56		1962.19	4.07
OC P1 P2 R	2037.69	1807.68	56.62	62.33		75.50	2002.13	-35.56
OC P1 PC R	2037.69	1807.68	56.62		35.56	75.50	1975.36	-62.33
OC P2 PC R	1958.13	1807.68		62.33	35.56	75.50	1981.07	22.94
OC P1 P2 PC R	2037.69	1807.68	56.62	62.33	35.56	75.50	2037.69	0.00
P1 P2 PC R	210.00		56.62	62.33	35.56	75.50	230.00	20.00
P2 PC R	210.00			62.33	35.56	75.50	173.38	-36.62
P1 PC R	60.00		56.62		35.56	75.50	167.67	107.67
P1 P2 R	150.00		56.62	62.33		75.50	194.45	44.45
P1 P2 PC	150.00		56.62	62.33	35.56		154.51	4.51
PC R	60.00				35.56	75.50	111.05	51.05
P2 R	150.00			62.33		75.50	137.82	-12.18
P2 PC	0.00			62.33	35.56		97.89	97.89
P1 R	0.00		56.62			75.50	132.12	132.12
P1 PC	150.00		56.62		35.56		92.18	-57.82
P1 P2	150.00		56.62	62.33			118.95	-31.05
R	0.00					75.50	75.50	75.50
PC	0.00				35.56		35.56	35.56
P2	0.00			62.33			62.33	62.33
P1	0.00		56.62				56.62	56.62

Table 6.4. Coalition Values for S2

players	v(S)	OC	P1	P2	PC	R	sum(yi)	sum(yi) - v(S)
OC	1940.63	1955.26					1955.26	14.64
OC P1	1940.63	1955.26	0.00				1955.26	14.64
OC P2	2095.63	1955.26		152.60			2107.86	12.24
OC PC	2024.69	1955.26			72.14		2027.40	2.71
OC R	1940.63	1955.26				0.00	1955.26	14.64
OC P1 P2	2095.63	1955.26	0.00	152.60			2107.86	12.24
OC P1 Pc	2024.69	1955.26	0.00		72.14		2027.40	2.71
OC P1 R	1940.62	1955.26	0.00			0.00	1955.26	14.64
OC P2 PC	2180.00	1955.26		152.60	72.14		2180.00	0.00
OC P2 R	2095.63	1955.26		152.60		0.00	2107.86	12.24
OC PC R	2024.69	1955.26			72.14	0.00	2027.40	2.71
OC P1 P2 PC	2180.00	1955.26	0.00	152.60	72.14		2180.00	0.00
OC P1 P2 R	2095.62	1955.26	0.00	152.60		0.00	2107.86	12.24
OC P1 PC R	2024.69	1955.26	0.00		72.14	0.00	2027.40	2.71
OC P2 PC R	2180.00	1955.26		152.60	72.14	0.00	2180.00	0.00
OC P1 P2 PC R	2180.00	1955.26	0.00	152.60	72.14	0.00	2180.00	0.00
P1 P2 PC R	210.00		0.00	152.60	72.14	0.00	224.74	14.74
P2 PC R	210.00			152.60	72.14	0.00	224.74	14.74
P1 PC R	60.00		0.00		72.14	0.00	72.14	12.14
P1 P2 R	150.00		0.00	152.60		0.00	152.60	2.60
P1 P2 PC	210.00		0.00	152.60	72.14		224.74	14.74
PC R	60.00				72.14	0.00	72.14	12.14
P2 R	150.00			152.60		0.00	152.60	2.60
P2 PC	210.00			152.60	72.14		224.74	14.74
P1 R	0.00		0.00			0.00	0.00	0.00
P1 PC	60.00		0.00		72.14		72.14	12.14
P1 P2	150.00		0.00	152.60			152.60	2.60
R	0.00					0.00	0.00	0.00
PC	60.00				72.14		72.14	12.14
P2	150.00			152.60			152.60	2.60
P1	0.00		0.00				0.00	0.00

Table 6.5. Coalition Values for S3

players	v(S)	OC	P1	P2	PC	R	sum(yi)	sum(yi) - v(S)
OC	1504.47	1589.57					1589.57	85.10
OC P1	1535.54	1589.57	80.82				1670.40	134.86
OC P2	1629.48	1589.57		63.94			1653.52	24.04
OC PC	1572.97	1589.57			31.82		1621.39	48.42
OC R	1930.75	1589.57				337.22	1926.79	-3.96
OC P1 P2	1660.54	1589.57	80.82	63.94			1734.34	73.80
OC P1 Pc	1604.04	1589.57	80.82		31.82		1702.22	98.18
OC P1 R	2055.00	1589.57	80.82			337.22	2007.62	-47.38
OC P2 PC	1697.97	1589.57		63.94	31.82		1685.33	-12.64
OC P2 R	1962.00	1589.57		63.94		337.22	1990.73	28.73
OC PC R	1947.87	1589.57			31.82	337.22	1958.61	10.73
OC P1 P2 PC	1729.04	1589.57	80.82	63.94	31.82		1766.16	37.12
OC P1 P2 R	2086.25	1589.57	80.82	63.94		337.22	2071.56	-14.69
OC P1 PC R	2072.13	1589.57	80.82		31.82	337.22	2039.43	-32.69
OC P2 PC R	1942.98	1589.57		63.94	31.82	337.22	2022.55	79.58
OC P1 P2 PC R	2103.37	1589.57	80.82	63.94	31.82	337.22	2103.37	0.00
P1 P2 PC R	463.40		80.82	63.94	31.82	337.22	513.80	50.40
P2 PC R	433.40			63.94	31.82	337.22	432.98	-0.42
P1 PC R	343.40		80.82		31.82	337.22	449.86	106.46
P1 P2 R	415.40		80.82	63.94		337.22	481.98	66.58
P1 P2 PC	162.00		80.82	63.94	31.82		176.58	14.58
PC R	313.40				31.82	337.22	369.03	55.63
P2 R	385.40			63.94		337.22	401.16	15.76
P2 PC	42.00			63.94	31.82		95.76	53.76
P1 R	295.40		80.82			337.22	418.04	122.64
P1 PC	132.00		80.82		31.82		112.64	-19.36
P1 P2	150.00		80.82	63.94			144.77	-5.23
R	265.40					337.22	337.22	71.82
PC	12.00				31.82		31.82	19.82
P2	30.00			63.94			63.94	33.94
P1	30.00		80.82				80.82	50.82

Table 6.6. Coalition Values for S4

players	v(S)	OC	P1	P2	PC	R	sum(yi)	sum(yi) -v(S)
OC	1633.37	1645.61					1645.61	12.24
OC P1	1664.44	1645.61	30.53				1676.15	11.71
OC P2	1757.38	1645.61		122.08			1767.70	10.32
OC PC	1700.62	1645.61			57.71		1703.32	2.70
OC R	1898.77	1645.61				265.40	1911.01	12.24
OC P1 P2	1788.44	1645.61	30.53	122.08			1798.23	9.79
OC P1 Pc	1731.69	1645.61	30.53		57.71		1733.85	2.17
OC P1 R	1929.84	1645.61	30.53			265.40	1941.55	11.71
OC P2 PC	1824.87	1645.61		122.08	57.71		1825.41	0.53
OC P2 R	2022.77	1645.61		122.08		265.40	2033.10	10.32
OC PC R	1966.02	1645.61			57.71	265.40	1968.72	2.70
OC P1 P2 PC	1855.94	1645.61	30.53	122.08	57.71		1855.94	0.00
OC P1 P2 R	2053.84	1645.61	30.53	122.08		265.40	2063.63	9.79
OC P1 PC R	1997.09	1645.61	30.53		57.71	265.40	1999.25	2.17
OC P2 PC R	2090.28	1645.61		122.08	57.71	265.40	2090.81	0.53
OC P1 P2 PC R	2121.34	1645.61	30.53	122.08	57.71	265.40	2121.34	0.00
P1 P2 PC R	463.40		30.53	122.08	57.71	265.40	475.72	12.32
P2 PC R	433.40			122.08	57.71	265.40	445.19	11.79
P1 PC R	343.40		30.53		57.71	265.40	353.64	10.24
P1 P2 R	415.40		30.53	122.08		265.40	418.01	2.61
P1 P2 PC	198.00		30.53	122.08	57.71		210.32	12.32
PC R	313.40				57.71	265.40	323.11	9.71
P2 R	385.40			122.08		265.40	387.48	2.08
P2 PC	168.00			122.08	57.71		179.79	11.79
P1 R	295.40		30.53			265.40	295.93	0.53
P1 PC	78.00		30.53		57.71		88.24	10.24
P1 P2	150.00		30.53	122.08			152.61	2.61
R	265.40					265.40	265.40	0.00
PC	48.00				57.71		57.71	9.71
P2	120.00			122.08			122.08	2.08
P1	30.00		30.53				30.53	0.53

Next, LC and MMC are calculated and the results are presented in Tables 6.7 and 6.8. Both LC and MMC results prove that the core is empty for scenarios S1 and S3 ($\varepsilon > 0$ and $\eta < 1$), while the core exists for S2 and S4 ($\varepsilon <= 0$ and $\eta >= 1$). The three methods are compared in Figures 6.1 to 6.4. The LC and the MMC give relatively similar profit allocations with the Shapley Value. These two solutions are also much easier to calculate compared with the Shapley value.

Table 6.7. Least Core for S1, S2, S3 and S4

Scenario	epsilon	P1	P2	R	PC	OC	Total
S1	62.32	56.52	31.16	85.36	31.16	1833.49	2037.69
S2	0.00	0.00	155.31	0.00	84.06	1940.62	2180.00
S3	24.91	95.09	31.25	335.21	42.03	1599.79	2103.37
S4	0.00	31.06	124.25	265.40	48.00	1652.62	2121.34
S1 ratio		0.03	0.02	0.04	0.02	0.90	1.00
S2 ratio		0.00	0.07	0.00	0.04	0.89	1.00
S3 Ratio		0.05	0.01	0.16	0.02	0.76	1.00
S4 Ratio		0.01	0.06	0.13	0.02	0.78	1.00

Table 6.8. Minmax Core for S1, S2, S3 and S4

Scenario	eta	P1	P2	R	PC	OC	Total
S1	0.9478222	89.01	53.16	92.72	53.16	1749.63	2037.69
S2	1	0.00	155.31	0.00	84.06	1940.62	2180.00
S3	0.9768657	117.22	49.03	327.46	46.89	1562.78	2103.37
S4	1	31.06	120.00	265.40	48.00	1656.87	2121.34
S1 ratio		0.04	0.03	0.05	0.03	0.86	1.00
S2 ratio		0.00	0.07	0.00	0.04	0.89	1.00
S3 Ratio		0.06	0.02	0.16	0.02	0.74	1.00
S4 Ratio		0.01	0.06	0.13	0.02	0.78	1.00

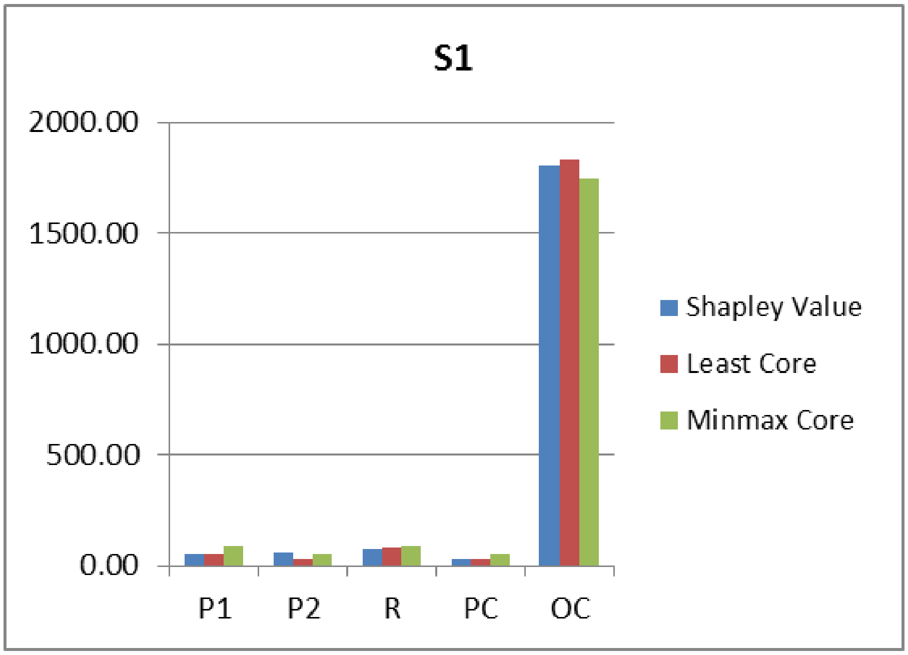

Figure 6.1. Comparisons of Shapley Value, LC, MMC for S1

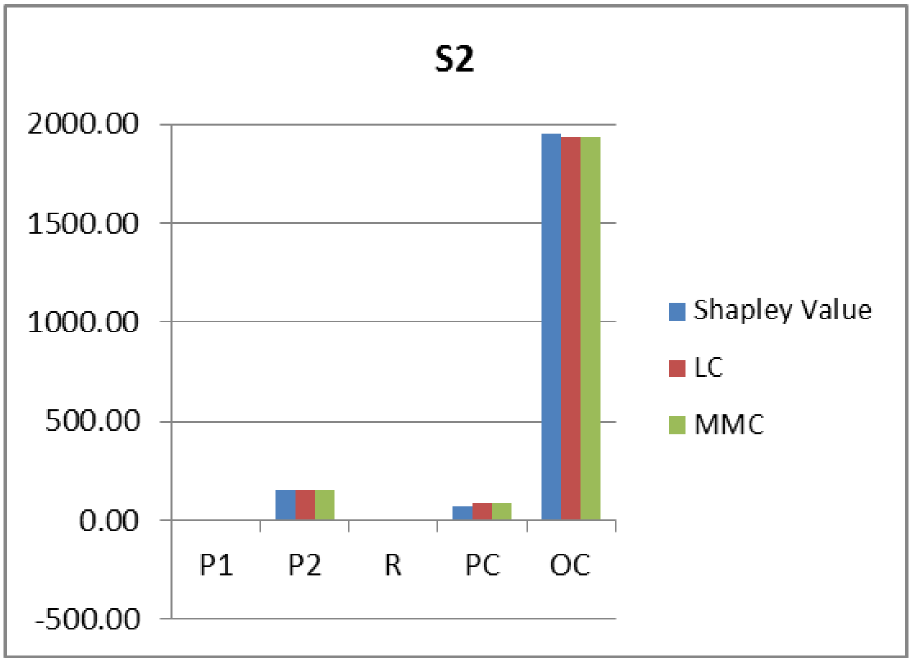

Figure 6.2. Comparisons of Shapley Value, LC, MMC for S2

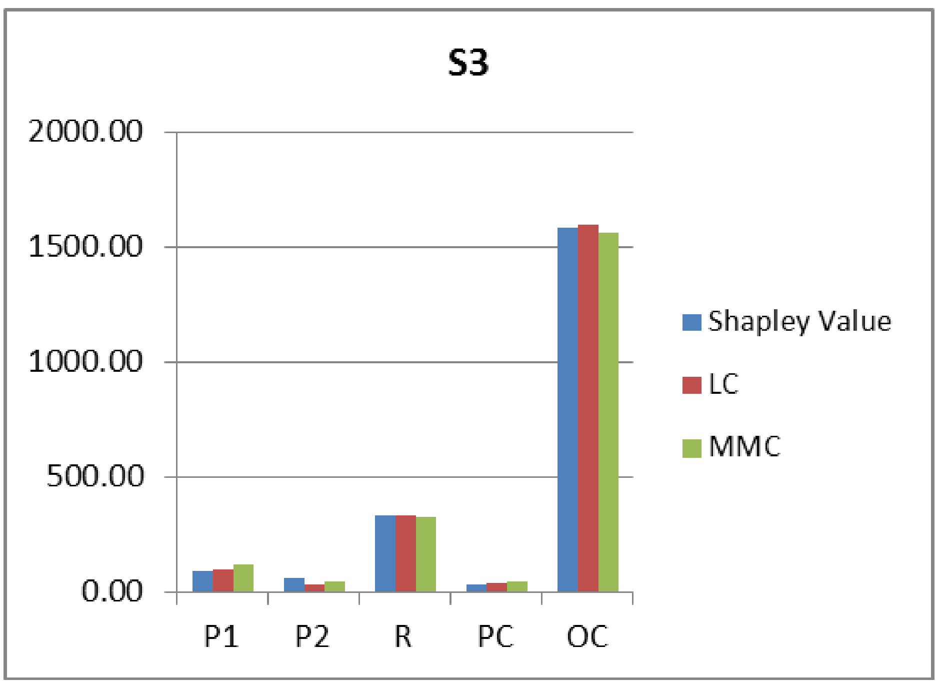

Figure 6.3. Comparisons of Shapley Value, LC, MMC for S3

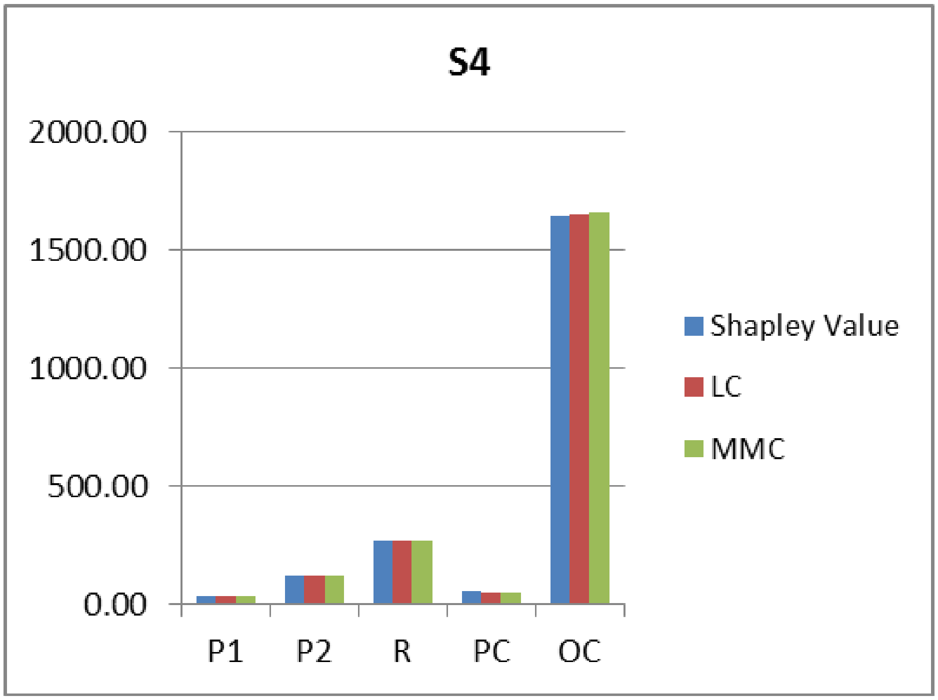

Figure 6.4. Comparisons of Shapley Value, LC, MMC for S4

6.2. Result Interpretation

Although the Shapley value solution is not in the core for all scenarios and two scenarios actually have an empty core, a close examination at the results and comparison of the scenario differences could reveal the relative market power of those players, their interacting relationships, and the reasons why the grand coalition is unstable.

In the Base Scenario (S1), the OC ships all containers via Terminal 1 and the railroad (West Coast route). Of the total $126,784,000 (1981*64,000) coalition profit, the OC gets 89%, the railroad gets 4%, the two terminals each get 3%, and the Canal gets 2%. Although OC ships zero containers to P2 and the Panama Canal in S1 (See Table B1), the Shapley value suggests that P2 and the Panama Canal still get positive profit allocations. Terminal 2 gets a total of $3,989,120 (62.33*64,000) and the Panama Canal gets $2,275,840 (35.56*64,000). These profit allocations are not a container handling revenue to the two players; instead, they are rewards to them for their willingness to cooperate. The total profit gained by OC, P1, and the railroad has to be shared with P2 and the Panama Canal, otherwise the OC may not ship via the WCR as in Model 0, Model 1, etc. Apparently, this allocation is hard to accept by the other players. As the core theory applies, the grand coalition in S1 is unstable. Some players would defect to a different coalition solution. In the next chapter, two small coalitions will be analyzed and compared to the grand coalition.

In the second scenario after the Panama Canal is expanded, the OC ships all containers via Terminal 2 and the Panama Canal. The total coalition profit increases, so does the profit share of the OC, P2, and PC. On the other hand, P1 and R get zero allocation. In S2, the grand coalition has an un-empty core, and the Shapley value is in the core.

Comparing S1 and S2 (Figure 6.5), the relative market powers of the Canal and the port on the East Coast (PC and P2) both increase after the Canal expansion is completed while the powers of the WCR players (P1 and R) both decrease. The OC's Shapley value also increases after the expansion, but in a smaller magnitude than the PC and P1.

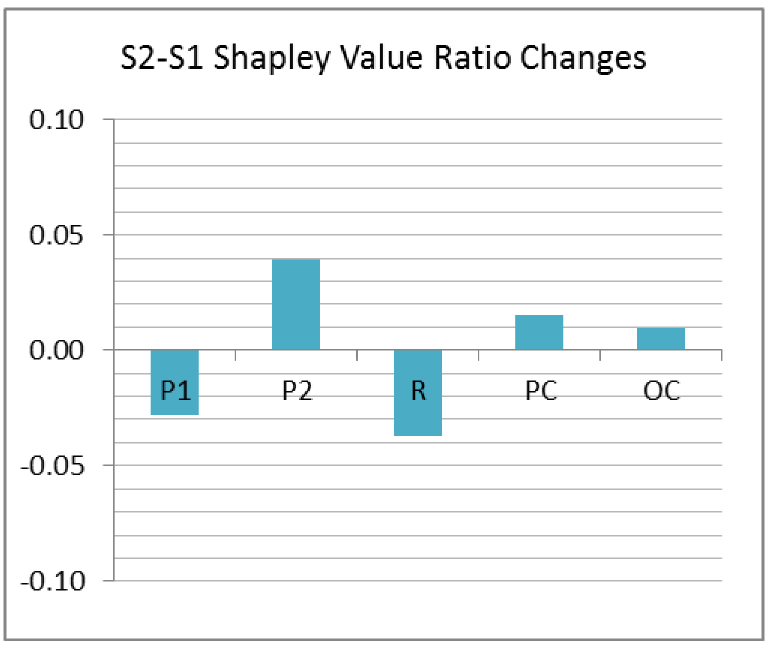

Figure 6.5. Panama Canal Expansion Impact S1 vs. S2

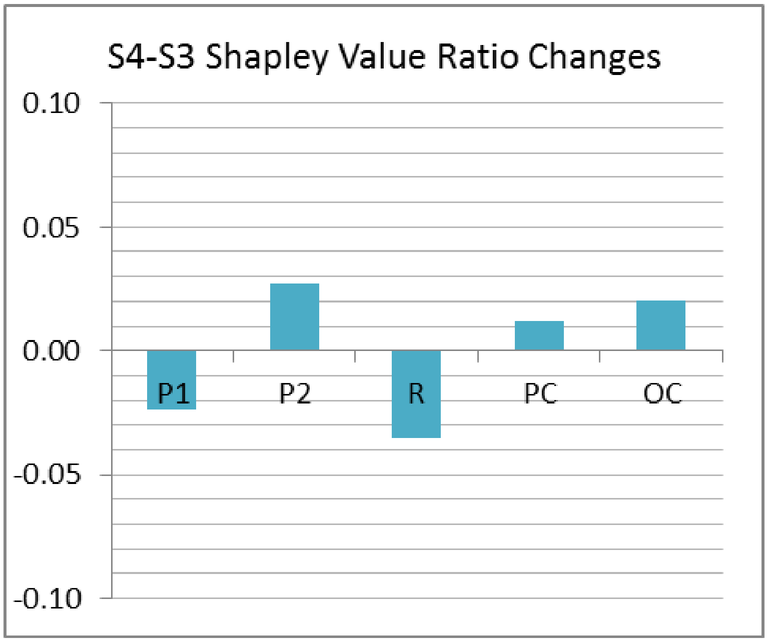

Figure 6.6. Panama Canal Expansion Impact S3 vs. S4

The capacity constraints will not change much of the impact of the Canal expansion (Figure 6.6). But under terminal capacity constraint assumption, the absolute values of the change for all players are smaller, except for the OC. A check on the unit profit value changes in Table 6.2 reveals, however, that the East Coast players (P2, PC) get smaller profits per FEU after the Canal is expanded, assuming there is not enough container handling capacity at the terminals. There are several reasons for this “unfair” result. One is the PC’s lower and upper bound rates have been assumed unchanged after the expansion, which is unrealistic. Another is that, as has been discussed in the previous section, the “before expansion” scenarios have an unstable grand coalition, and the Shapley value allocations to the EC players could be hardly realized in practice.

Finally, Figures 6.7 and 6.8 are created to illustrate the impact of capacity constraint assumption. It seems that the capacity constraint has opposite effects on the Shapley values of the OC and the railroad. When both terminals do have not enough resources to handle all shipments, the OC loses profits while the railroad gains more.

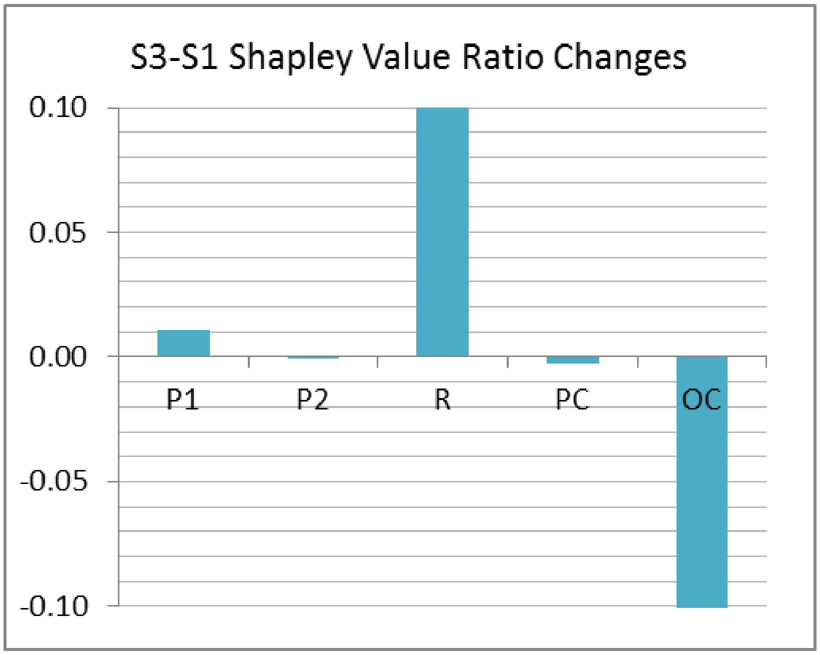

Figure 6.7. Terminal Capacity Constraint Impact S1 vs. S3

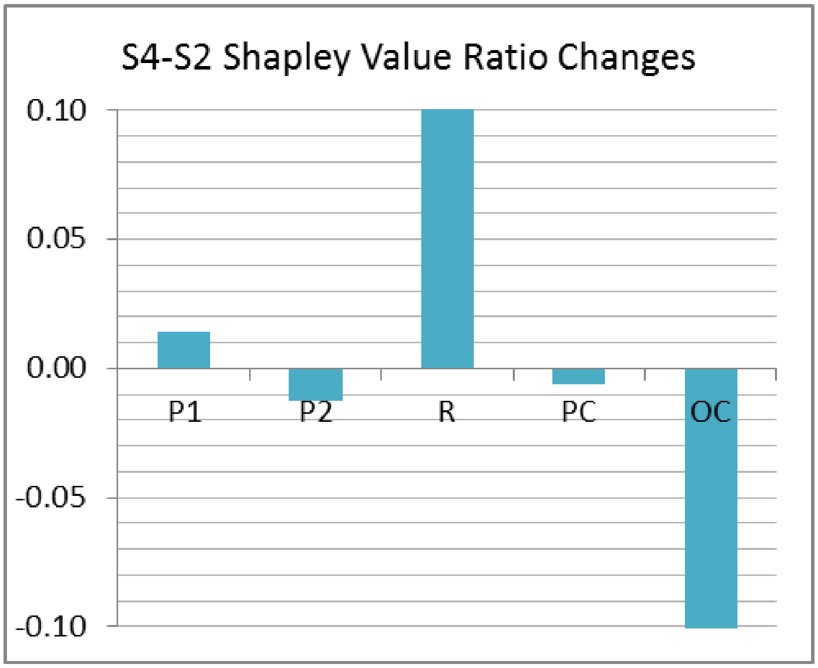

Figure 6.8. Terminal Capacity Constraint Impact S2 vs. S4

Both LC and MMC results prove that the core is empty for scenarios S1 and S3 ($\varepsilon > 0$ and $\eta < 1$), while the core exists for S2 and S4 ($\varepsilon <= 0$ and $\eta >= 1$). An empty core indicates the grand coalition is not stable, in the sense that there is no allocation solution that is not dominated by other solutions, so that at least one player will defect to a different coalition, causing the grand coalition to deform. In this case study, the ocean carrier is the dominant player and has two route choices, causing the competition between the two routes unavoidable. Actually, a close look at the S2 results reveals the reason that they could form a stable grand coalition in S2 is because the OC always chooses the ECR no matter what kind of coalition is formed, and all allocation methods (Shapley Value, LC, MMC) assign zero profits to the WCR players. Later it is found that by changing some parameter values the results could change easily. Overall, the grand coalition of the five players is very unstable.

6.3. Sensitivity Analysis

This section presents a sensitivity analysis on some model parameter values, and discusses their impacts on the roles of the players in the container shipping market. The analysis is based on the base scenario S1.The first parameter to be analyzed is the inventory cost difference. In the model, the inventory cost is not directly included in the OC's cost function, because it is a cost to shippers. The shippers with higher valued goods are willing to pay more in order to get quicker delivery. The shippers' perceptions of delivery speed are reflected by the OC's charging rates. In order to charge more, the OC chooses a quicker route (WCR). The difference between the two charging rates (R_1 for WCR vs. R_2 for ECR) is the average unit inventory cost difference between the two routes.

6.3.1. Impacts of Cargo Values

Using the average value of $21.66 per cubic foot for containerized import from Asia to United States and $56 per FEU for daily pipeline inventory cost (DPV), the total inventory cost difference between the two routes currently is $371 per FEU. After the expansion is finished, the difference will be reduced to $220 per FEU. The inventory cost increases with higher cargo values, which makes the quicker route more attractive to shippers. To capture the impact of the cargo values on the route choice and profit allocation, the models are re-calculated by changing DPV value to 30, 40, 56, or 70 dollars/FEU. The players' Shapley values and Shapley value ratios are presented in Figures 6.9 and 6.10. Generally, with higher values of the containerized cargo, both absolute Shapley values and the relative ratios of the WCR players get higher while those of the ECR players decrease. This is consistent with the fact that the WCR is preferred for higher-valued cargoes. As for the OC, its profit increases with the cargo value, but its sharing percentage of the total profit does not necessarily follow suit.

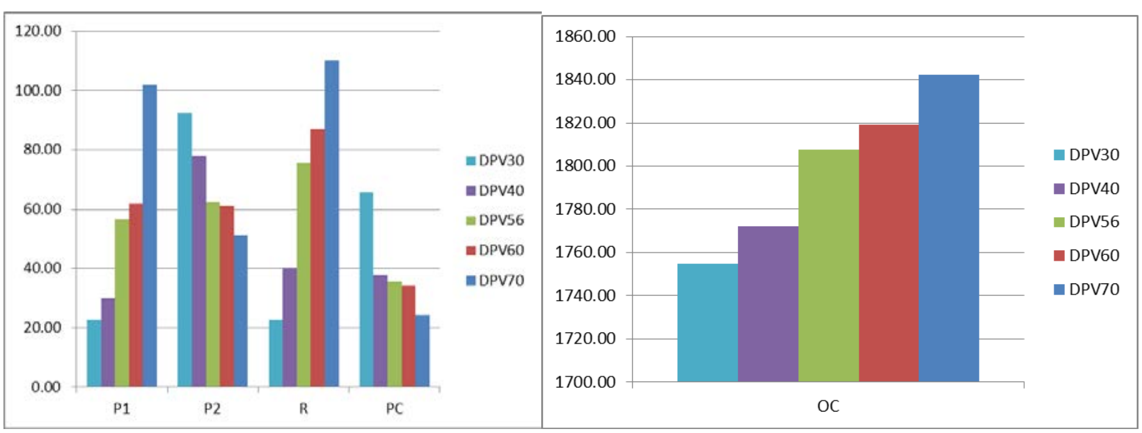

Figure 6.9. Shapley Value Changes with Cargo Values in S1

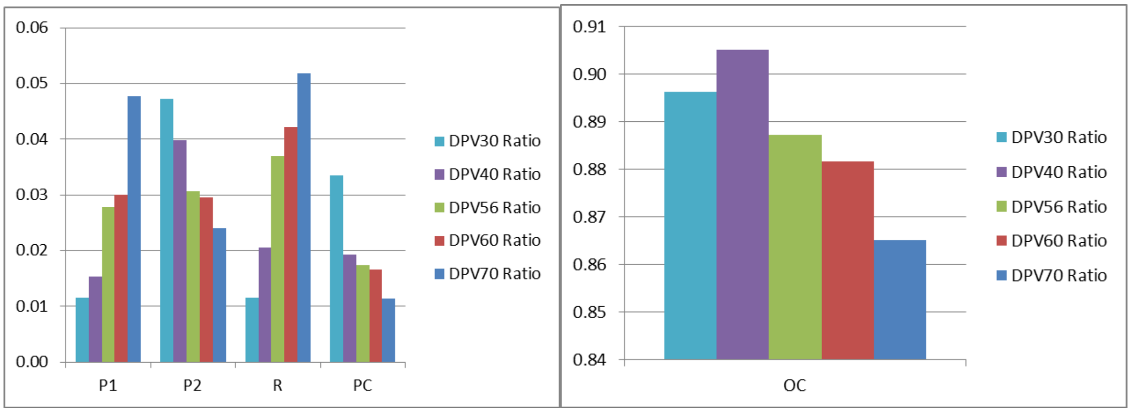

Figure 6.10. Shapley Value Ratio Changes with Cargo Values in S1

6.3.2. Impacts of Charging Rates

The lower and upper bounds of charging rates by the Panama Canal and the railroad are studied in the same way by changing 10% from the base case. The lower bound of the rate is the player's cost of handling one unit of container, or the lowest rate the player is willing to accept to handle one unit of container. The upper bound is the highest rate the player could charge under non-cooperative assumption. The results are shown in Figure 6.11 to Figure 6.17.

When the railroad cost decreases, the absolute Shapley value and the ratio of the value for the railroad increase while those values and ratios for P2 and PC decrease (Figure 6.11 and Figure 6.12). The OC seems to get higher profit with reduced railroad cost, but its share of the total profit actually gets smaller. Terminal 1's shared profit first increases then decreases, which is probably because of the two-sided effect of railroad cost. When the railroad cost is reduced, the WCR benefits as a group, but the relative power of Terminal 1 compared with the railroad also gets weaker. So when the railroad cost decreases to a certain value, the benefits gained by P1 is less significant than the lost power to the railroad.

The railroad rate upper bound has almost no impact until it is lowered to 50% of the original base case value (Figure 6.13). The railroad and the EC players get smaller profits, while the OC and P1 get more profits. The ratios of the sharing follow the same pattern (Figure 6.14).

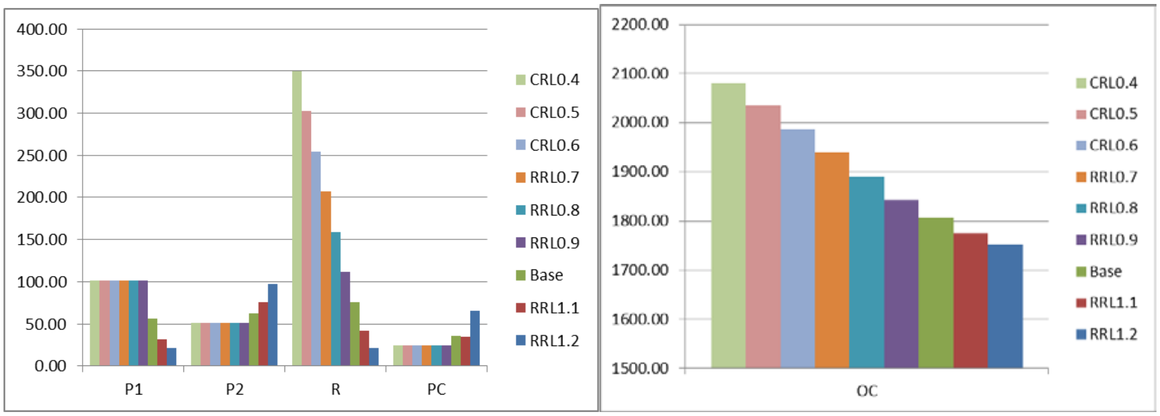

Figure 6.11. Shapley Value Changes with Railroad Rate Lower Bound in S1

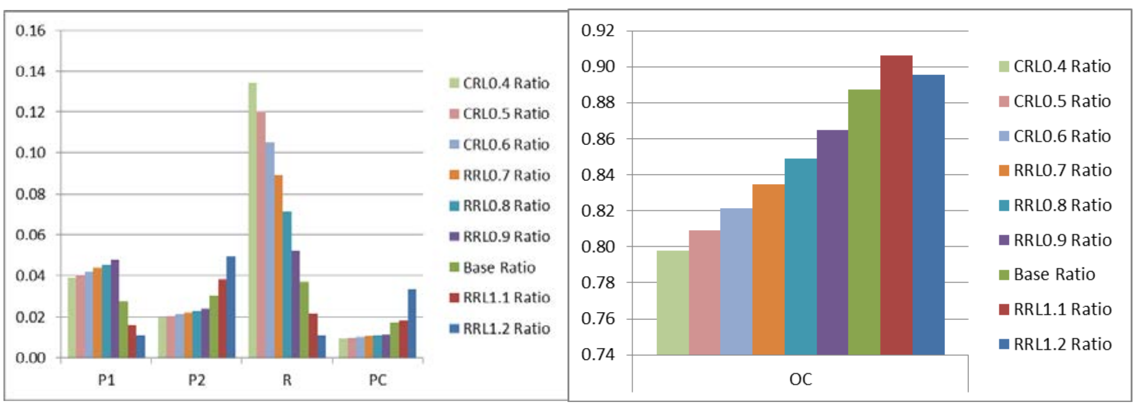

Figure 6.12. Shapley Value Ratios Changes with Railroad Rate Lower Bound in S1

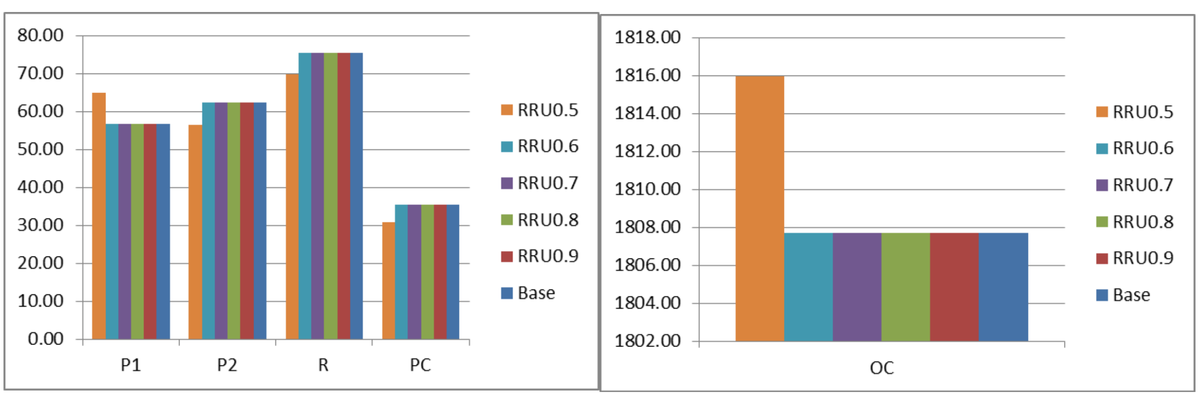

Figure 6.13. Shapley Value Changes with Railroad Rate Upper Bound in S1

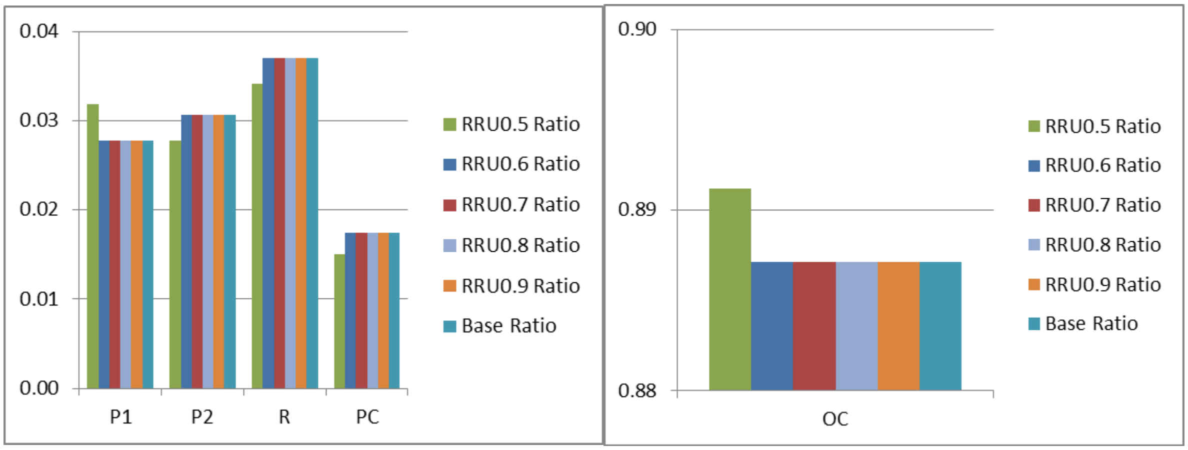

Figure 6.14. Shapley Value Ratio Changes with Railroad Rate Upper Bound in S1

As for the Canal charging rate, the effect of changing lower and upper bound is very different from the railroad. The ECR players' Shapley values increase while the WCR players and the OC's profits decrease with the Canal's cost decrease initially. However, when the lower bound of the Canal rate further decreases to below 50% of the base-case assumption value ($160/FEU), the railroad's profit starts to increase (Figure 6.15). The ratio changes follow the same pattern (Figure 6.16).

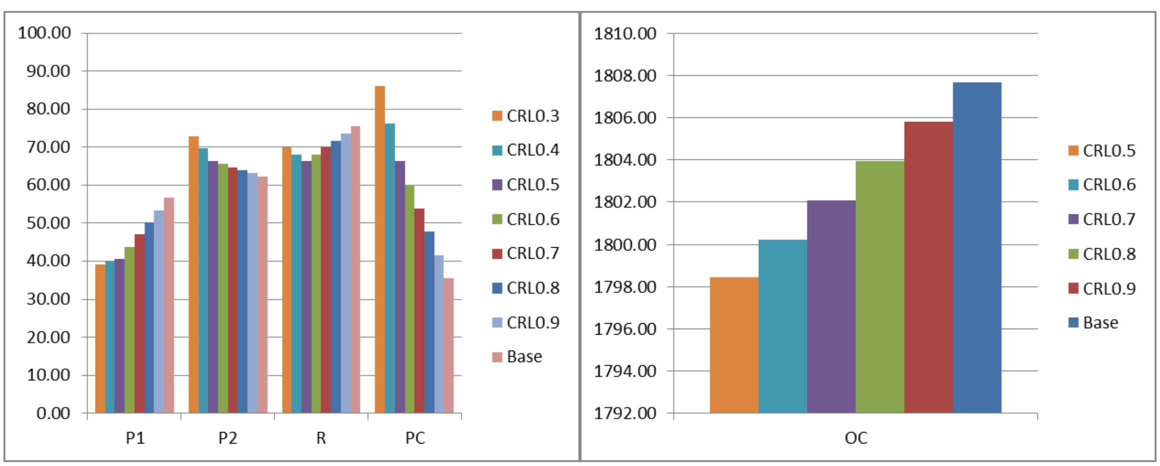

Figure 6.15. Shapley Value Changes with Panama Canal Rate Lower Bound in S1

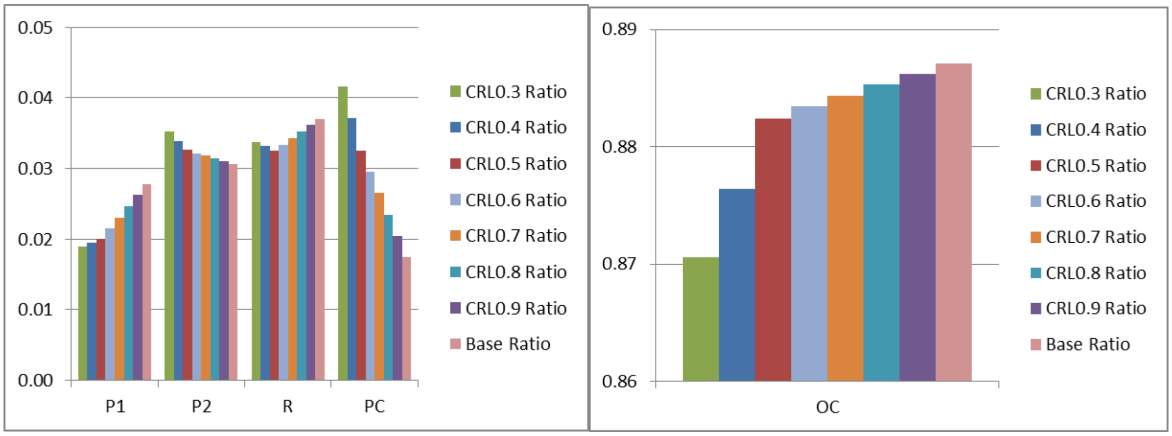

Figure 6.16. Shapley Value Ratio Changes with Panama Canal Rate Lower Bound in S1

When the Canal rate's upper bound increases from 80% to 130% of base case assumption, the Shapley values of railroad and the Canal both increase gradually; the OC's Shapley value decreases gradually; and the two terminals have no change (Figure 6.17). The ratio changes follow exactly the same pattern (Figure 6.18). In the end, the OC's charging rate is also analyzed. Figure 6.19 clearly shows the OC's rate only has impact on its own profit.

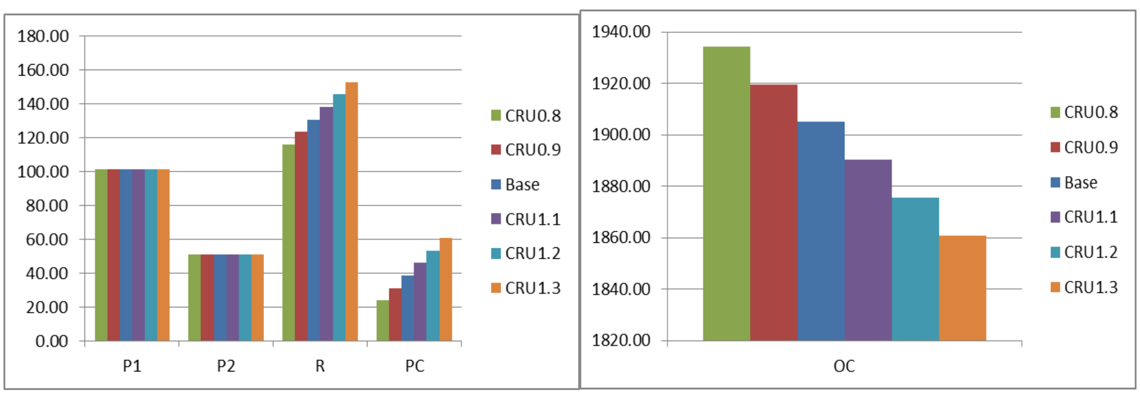

Figure 6.17. Shapley Value Changes with Panama Canal Rate Upper Bound in S1

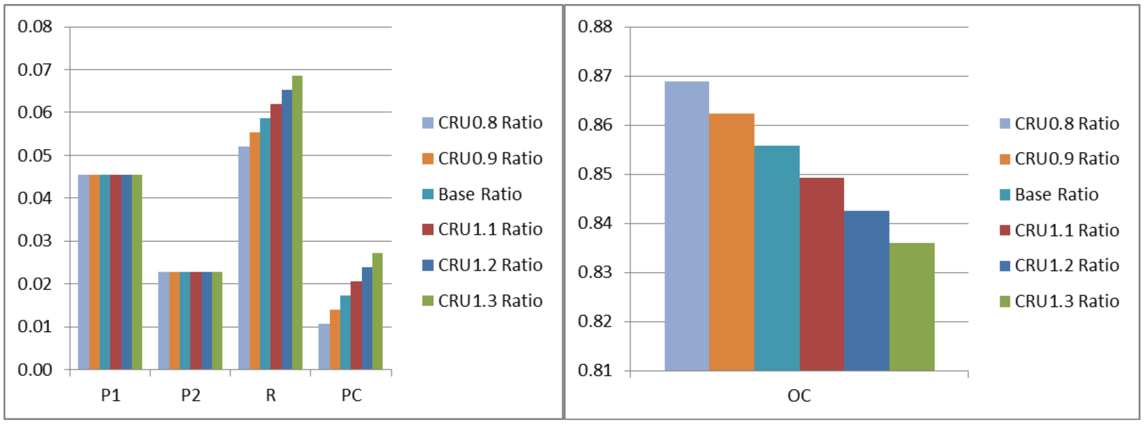

Figure 6.18. Shapley Value Ratio Changes with Panama Canal Rate Upper Bound in S1

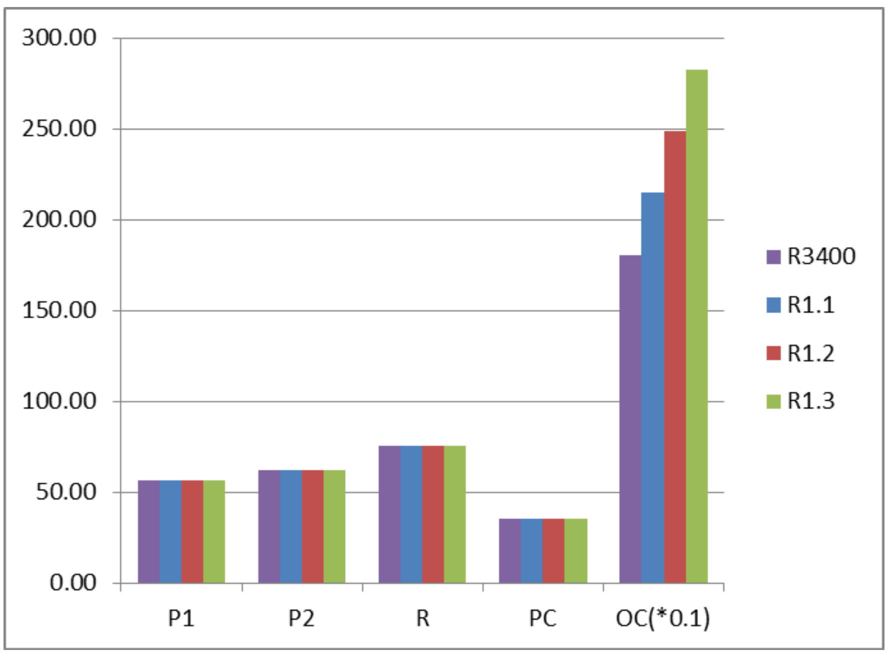

Figure 6.19. Shapley Value Changes with OC Rates in S1

6.3.3. *Impacts of Capacity Constraint Assumption*

In the end, the assumption of capacity constraint at the terminals is also analyzed by varying the capacity level at the terminals. Assuming each terminal could handle 90% or 70% of total shipment volume of the OC, the Shapley value ratios are compared with the original values with 80% of capacity constraints. Figure 6.20 and Figure 6.21 show how the Shapley values and Shapley value ratios change for each player when the capacity at the terminals changes. Again, the capacity constraints clearly have positive impact on the railroad market power and negative impact on the OC. For the other players, the impact is not linear.

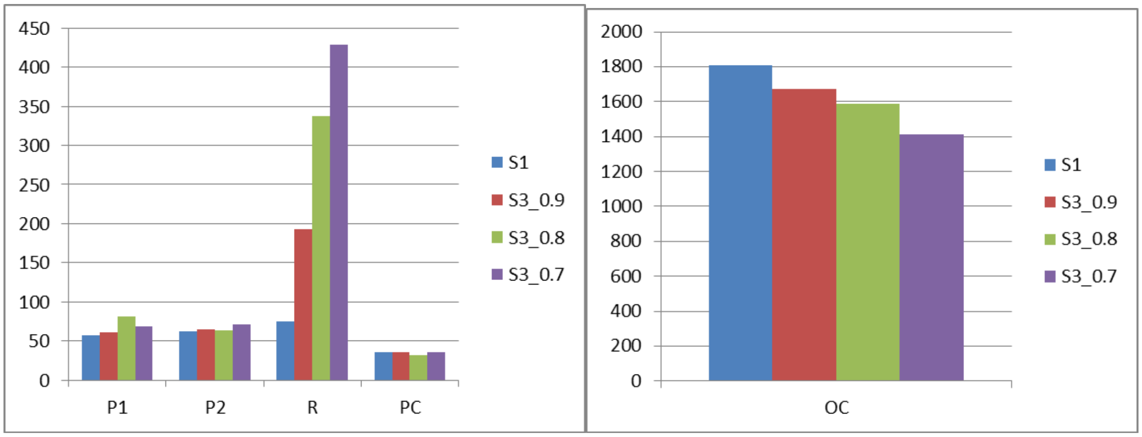

Figure 6.20. Shapley Value Changes with Terminal Capacity Constraints

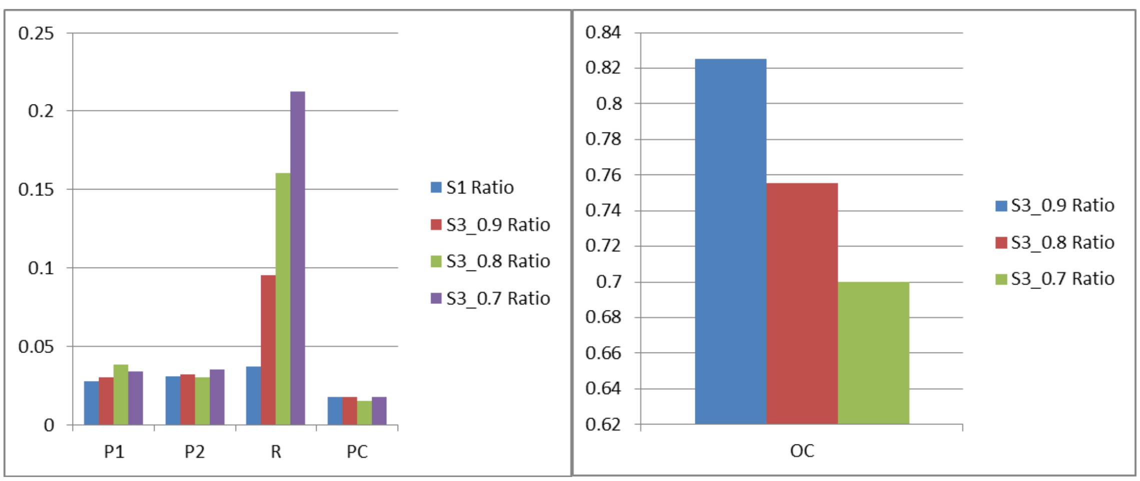

Figure 6.21. Shapley Value Ratio Changes with Terminal Capacity Constraints

6.4. Conclusions of Case Study

Four scenarios are conducted, and the model results indicate that if the grand coalition of the five players is to form, the OC will ship all or most (depending on if there is enough capacity) via the WCR before the Canal expansion. After the expansion is finished and both routes are served by the 8,000-TEU vessel, the OC will prefer the all-waterway route via the Panama Canal directly to the East Coast because of the higher profit.

When there is capacity constraint at the port terminals, the railroad gains more power while the OC loses profit due to the constraints. Even assuming that both terminals could handle the same amount of containers, the capacity constraint impact on the two terminals is not clear. The Panama Canal's impact on the relative power of the players is much more direct. The EC benefits mostly, with OC's profits increasing at a smaller degree, while the WC players lose power due to the increasing power of their competitors.

The sensitivity analysis of some parameters in Scenario1 shows that the Shapley values and value ratios of the five players are very sensitive to most parameter values. Although some changes are very easy to expect, some are not very straightforward. Even with only five players and two route choices, the interacting relationships are so complicated that the game results are hard to predict without the help of model calculation.

Some general findings could still be drawn from the analysis of Scenario 1. If a player could reduce its lower-bound rate (cost), that helps it gain more power in the coalition and get a higher profit allocation. The impacts on other players are not very obvious. Although the OC's relative ratio decreases with reduced rail cost because it loses power to railroad, its absolute profit improves. On the other hand, both the profit value and the portion of the OC get worse when the Canal's cost decreases. Regarding the different impacts of railroad cost and Canal cost on the OC, one explanation is that in Scenario 1 the OC ships through WCR. Thus, lowering the railway cost helps the coalition overall as well as the OC. Lowering the Canal cost, on the other hand, does not save the grand coalition extra cost.

Another pattern of the cost impact is that the same route players' profits change in the same direction while different-route players' profits change in the opposite direction. However, this is only for the case with only two routes. When a player is involved in more than one route, it is hard to define its partners or competitors. For this case study, if a transportation operator could reduce its cost, it helps increase itself and its partner's market power. Depending on if it handles any containers for the OC, the cost reduction may or may not help the OC's profit.

The highest possible rate the player could charge generally reflects its relative market power. It works as a threat to the OC in that the OC has to pay a certain price level if no cooperation happens. But it also increases its competitors' profit or does not benefit itself at all, as the railroad and the canal rate analyses show.

When the average cargo value of the container increases, the inventory cost difference between the two routes also increases. This makes the WCR a more profitable choice for the OC, and the competitive powers of the WCR players generally increase.

Most of the findings are consistent with real world practice and expectations. Some results that are tricky to explain further prove that the shipping market is complicated and many factors are making an effect at the same time. The cooperative game solutions offer a measurable tool to understand interactive relationships in the ocean shipping industry, to compare the relative powers of players, and to make predictions of market equilibrium.

The Least core (LC) and Minmax core (MMC) are calculated; and they produce very similar results with the Shapley value. The advantages of LC and MMC are that they are much easier to compute and they also seek a fairness solution. Of the four scenarios, S1 and S3, which assume the current status of unfinished Panama-Canal-expansion, both have an empty core. By changing some parameter values, the results could change easily. Overall, the grand coalition of the five players is very unstable. The main reason is because, essentially, with only one ocean carrier, the competition between the two routes is unavoidable. In the next chapter, two following games are created supposing the grand coalition does not form.

7. FOLLOWING GAMES

7.1. West Coast Coalition and East Coast Coalition

As concluded in Chapter 6, the grand coalition of the five players is unstable because of the competitive nature between the two routes. In this chapter, two separate possible coalitions are derived and tested: the West Coast coalition (WCC) {OC, P1, R} and the East Coast coalition (ECC) {OC, P2, PC}. Assuming the grand coalition could not form, the OC either cooperates with P1 and R, or cooperates with P2 and PC. Only S1 and S2 are used for illustration. The model results are given in Appendix C Table C1, C2, C3, and C4. The Shapley values are presented below in Tables 7.1 and 7.2.

Table 7.1. Shapley Values and Value Ratios for West Coast Coalition {OC, P1, R}

	P1	R	OC	Total profit
S1: West	152.656	1,327.000	558.031	2,037.687
S2: West	152.656	1,327.000	407.031	1,886.687
S1 Ratio: West	0.075	0.651	0.274	1.000
S2 Ratio: West	0.081	0.703	0.216	1.000

Table 7.2. Shapley Values and Value Ratios for East Coast Coalition {OC, P2, PC}

	P2	PC	OC	Total profit
S1: East	153.125	72.813	1732.187	1958.125
S2: East	152.552	72.083	1955.208	2179.844
S1 Ratio: East	0.078	0.037	0.885	1.000
S2 Ratio: East	0.070	0.033	0.897	1.000

Similarly, as in Chapter 6, all values are divided by 64,000 for the purpose of easier presenting and interpreting. For the small coalitions, the Shapley value could be directly interpreted as a unit profit per FEU for every player. Tables 7.3 to 7.6 prove that all the Shapley value solutions are in the core (One small negative value in Table 7.6 is a rounding error.) Both coalitions are stable since the core exists. Apparently the ECC is preferred by the OC, because it allocates higher profits for the OC. So the ECC will be studied in detail in this chapter.

Table 7.3. West Coast Coalition Values in S1

Players	v(S)	OC	P1	R	sum(yi)	sum(yi) -v(S)
OC	555.38	558.03			558.03	2.66
OC P1	710.69	558.03	152.66		710.69	0.00
OC R	1882.38	558.03		1327.00	1885.03	2.66
OC P1 R	2037.69	558.03	152.66	1327.00	2037.69	0.00
P1 R	1477.00		152.66	1327.00	1479.66	2.66
R	1327.00			1327.00	1327.00	0.00
P1	150.00		152.66		152.66	2.66

Table 7.4. West Coast Coalition Values in S2

Players	v(S)	OC	P1	R	sum(yi)	sum(yi) -v(S)
OC	404.38	407.03			407.03	2.66
OC P1	559.69	407.03	152.66		559.69	0.00
OC R	1731.38	407.03		1327.00	1734.03	2.66
OC P1 R	1886.69	407.03	152.66	1327.00	1886.69	0.00
P1 R	1477.00		152.66	1327.00	1479.66	2.66
R	1327.00			1327.00	1327.00	0.00
P1	150.00		152.66		152.66	2.66

Table 7.5. East Coast Coalition Values in S1

Players	v(S)	OC	P2	PC	sum(yi)	sum(yi) -v(S)
OC	1716.25	1732.19			1732.19	15.94
OC P2	1872.50	1732.19	153.13		1885.31	12.81
OC PC	1801.88	1732.19		72.81	1805.00	3.13
OC P2 PC	1958.13	1732.19	153.13	72.81	1958.13	0.00
P2 PC	210.00		153.13	72.81	225.94	15.94
PC	60.00			72.81	72.81	12.81
P2	150.00		153.13		153.13	3.13

Table 7.6. East Coast Coalition Values in S2

Players	v(S)	OC	P2	PC	sum(yi)	sum(yi) -v(S)
OC	1940.63	1955.21			1955.21	14.58
OC P2	2095.63	1955.21	152.55		2107.76	12.14
OC PC	2024.69	1955.21		72.08	2027.29	2.60
OC P2 PC	2180.00	1955.21	152.55	72.08	2179.84	-0.16
P2 PC	210.00		152.55	72.08	224.64	14.64
PC	60.00			72.08	72.08	12.08
P2	150.00		152.55		152.55	2.55

The ECC gets slightly lower total profit than the grand coalition. In S1, both P2 and PC get better results in the ECC than in the grand coalition, although the OC actually gets less. In S2, all the players in ECC get almost the same as the result in the grand coalition game.

Every player in the small coalition gains extra profit compared with playing as singletons. For example, as shown in Table 7.5, the OC gains an extra $15.94 per FEU, the PC gains an extra $12.81 per FEU, and P2 gains an extra $3.13 per FEU, compared with playing individually against the rest of players. The total extra profit gained by all three players in the ECC is $31.88 per FEU. To prove that this amount is the exact total gain of this coalition due to the cooperating benefit, the coalition value is estimated again assuming there is no benefit of cooperating, i.e., no transit time saving. Results are pasted in Appendix C Table C5. The results are compared in Table 7.7 below. The cooperation of the three players adds a total of $31.88 per FEU to the coalition profit, assuming transit time is saved 0.5 days at the terminal and at the Canal. This benefit gained by the coalition is allocated to each player based on Shapley value calculation rules.

Table 7.7. Shapley Value Changes Due to Cooperation of ECC in S1

	P2	PC	OC	Total profit
S1:Cooperation Benefit	153.125	72.813	1732.187	1958.125
S1: No-Cooperation Benefit	150.000	60.000	1716.250	1926.250
S1 Changes	3.125	12.813	15.938	31.875

The Shapley Value is by far the most popular allocation method in cooperative game theory. Of the total profit of $1,958.125 for the coalition in Scenario 1, P2 gets a profit of $153.125, the PC gets a profit of $72.813, and the OC gets the rest. Considering the cost of $150 per FEU for P2 and $160 per FEU for PC, that means the OC would pay $303.125 per FEU to P2 and $232.813 per FEU to PC. Note the highest rates charged by the two players under non-cooperative assumption are $300 and $220 per FEU, respectively. The collaboration between the three players saves transit time and operating cost for the OC. The cooperative game theory proves that when the three players negotiate prices, the terminal and the Canal actually get more than the amount they would charge if no cooperation exists, but the OC still benefits because the cost saved from cooperating is more than the extra amount it pays to other players. How much of the benefit the OC has to return to the other two players depends on the relative market powers of the three players. In order to have a stable coalition, the division of total benefits has to be un-dominated by any other allocation method. When the Shapley value is in the core, the allocation method is un-dominated and stable.

Comparing the before and after expansion scenario results (S1 vs. S2), the benefit of using a larger vessel is mostly gained by the OC. The Canal, on the other hand, has almost no change of profit. The reason for this “unfair” result is partly because in Scenario 2, the lower and upper bound of the Canal rate is assumed as unchanged. In reality, it is expected the Canal should increase both its cost and maximum charging rates. In the next section, sensitivity analysis on the Canal’s cost and rate are conducted to analyze how those values will affect the Canal’s role in the coalition.

Least core and Minmax core are also calculated (Table 7.8, 7.9). Similarly, like the grand coalition, both methods produce very similar results to the Shapley value solutions for the ECC (Figure 7.1, 7.2). Clearly, the core exists for ECC in both S1 and S2.

Table 7.8. Least Core for ECC in S1

Scenario	epsilon	P2	PC	OC	Total profit
S1	-3.125	153.125	82.500	1722.500	1958.125
S2	-2.656	152.656	81.719	1945.625	2180.000

Table 7.9. Minmax Core for ECC in S1

Scenario	eta	P2	PC	OC	Total profit
S1	1.003	150.480	79.629	1728.016	1958.125
S2	1.002	150.366	79.256	1950.378	2180.000

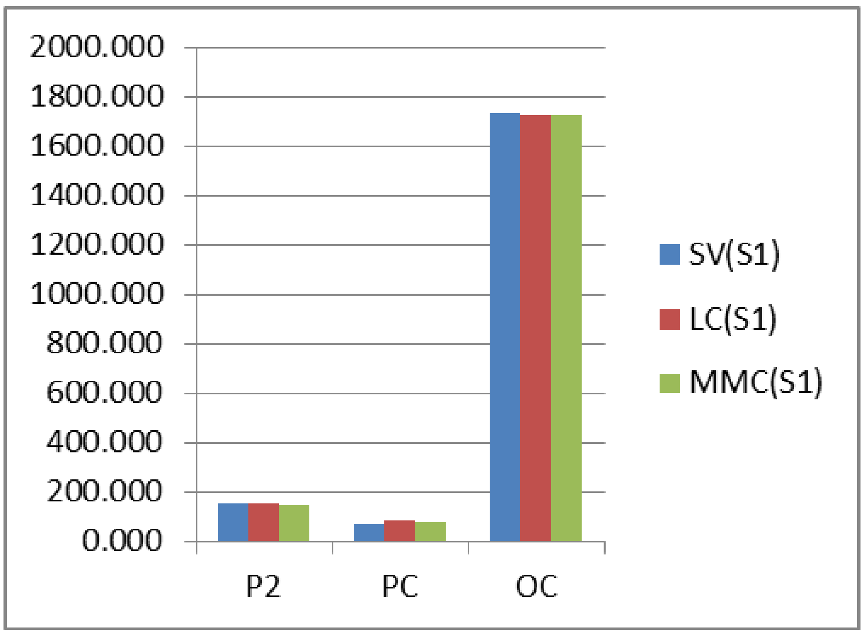

Figure 7.1. Comparisons of Shapley Value, LC, MMC for ECC in S1

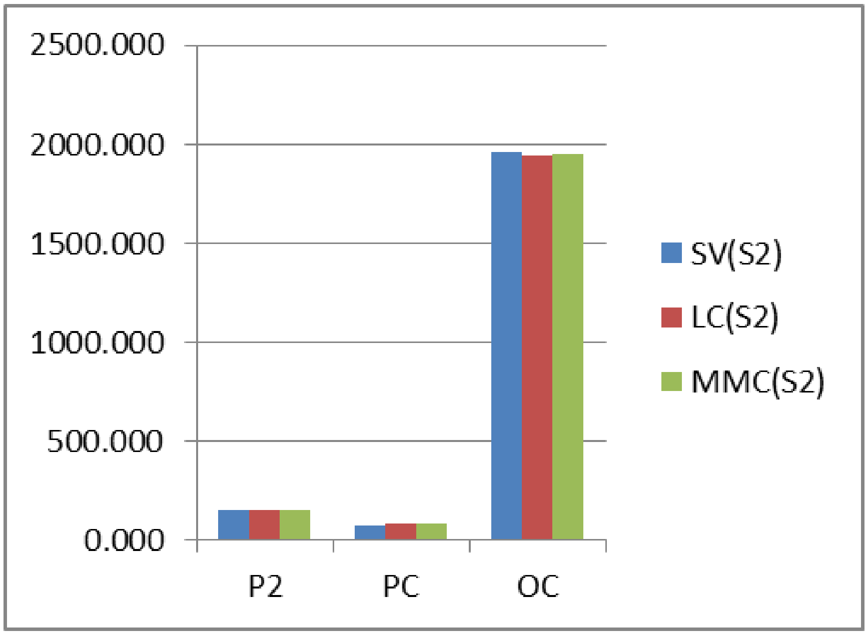

Figure 7.2. Comparisons of Shapley Value, LC, MMC for ECC in S2

7.2. Sensitivity Analysis for the Following Games

Sensitivity analysis on some parameter values is conducted for the ECC. The cost of Terminal 2 and the Canal are analyzed first. Decreasing the Canal cost (CRL) by $16 per FEU will increase its Shapley value by exactly $16 per FEU (Table 7.10). Similarly, decreasing Terminal 2's cost (PRL_2) by $15 per FEU will increase its allocated profit by $15 per FEU (Table 7.11). The cost reduction has benefit to the whole coalition, but all the benefit is allocated to the player itself.

Table 7.10. Shapley Value Changes with PC Lower Bound Rate in S1

	P2	PC	OC
CRL0.5	153	153	1732
CRL0.6	153	137	1732
CRL0.7	153	121	1732
CRL0.8	153	105	1732
CRL0.9	153	89	1732
Base	153	73	1732

Table 7.11. Shapley Value Changes with P2 Lower Bound Rate in S1

	P2	PC	OC
PRL0.5	228	73	1732
PRL0.6	213	73	1732
PRL0.7	198	73	1732
PRL0.8	183	73	1732
PRL0.9	168	73	1732
Base	153	73	1732

As shown in Table 7.12, increasing the Canal rate upper bound (CRU) by 1% ($22 per FEU) will increase its Shapley value by 1% ($22 per FEU) and decrease the OC's value by the same amount. Terminal 2 is not impacted. The same impact of changing the terminal upper bound rate (PRU_2) happens (Table 7.13). That is because the rate is a side payment inside the coalition, and has no impact on the coalition's value.

Table 7.12. Shapley Value and Ratio Changes with PC Upper Bound Rate in S1

	P2	PC	OC
CRU0.8	153.13	28.81	1776.19
CRU0.9	153.13	50.81	1754.19
Base	153.13	72.81	1732.19
CRU1.1	153.13	94.81	1710.19
CRU1.2	153.13	116.81	1688.19
CRU1.3	153.13	138.81	1666.19
CRU0.8 Ratio	0.08	0.01	0.91
CRU0.9 Ratio	0.08	0.03	0.90
Base Ratio	0.08	0.04	0.88
CRU1.1 Ratio	0.08	0.05	0.87
CRU1.2 Ratio	0.08	0.06	0.86
CRU1.3 Ratio	0.08	0.07	0.85

Table 7.13. Shapley Value and Ratio Changes with P2 Upper Bound Rate in S1

	P2	PC	OC
PRU0.8	93.13	72.81	1792.19
PRU0.9	123.13	72.81	1762.19
Base	153.13	72.81	1732.19
PRU1.1	183.13	72.81	1702.19
PRU1.2	213.13	72.81	1672.19
PRU1.3	243.13	72.81	1642.19
PRU0.8 Ratio	0.05	0.04	0.92
PRU0.9 Ratio	0.06	0.04	0.90
Base Ratio	0.08	0.04	0.88
PRU1.1 Ratio	0.09	0.04	0.87
PRU1.2 Ratio	0.11	0.04	0.85
PRU1.3 Ratio	0.12	0.04	0.84

As discussed in the previous section, the OC's payment to the Canal is higher than the Canal's upper-bound rate. Increasing the upper-bound value increases the payment at the same rate, and narrows the profit ratio between the Canal and the OC. Reducing the lower bound value, on the other hand, not only increases the Canal's profit and profit ratio to the OC, but also increases the total coalition's profit. In conclusion, the lower-bound value, representing the cost of the player, could reflect a player's absolute attribution to any coalition. The upper bound value somehow reflects the player's relative market power to other players. So far, lowering the cost of a player (PC or P2) and increasing its upper bound rate both help improve its Shapley value.

When the expansion is finished, it is expected that the Panama Canal will have both higher costs and higher rates. To obtain a clearer understanding of the Panama Canal expansion's impact, Scenario 2 is used to conduct another sensitivity study of the changing impact of these two factors simultaneously. Table 7.14 shows how the Shapley Value would change when both the lower and upper bounds of the Canal rate are increased by 1% in S2. The PC will get $6 per FEU more when the lower bound is increased by $16 and the upper bound is increased by $22 per FEU. The OC will get $22 per FEU less due to the increase of the upper bound rate. Table

7.15 shows how the Shapley Value would change when both the lower and upper bounds of Terminal 2 rate are increased by 1% in S2. P1 will get $15 per FEU more when the lower bound is increased by $15 and the upper bound is increased by $30 per FEU. The OC will get $30 less due to the increase of the upper bound rate.

Table 7.14. Shapley Value and Ratio Changes with CRL and CRU in S2

	P2	PC	OC
CRLCRU1.3	152.55	90.08	1889.21
CRLCRU1.2	152.55	84.08	1911.21
CRUCRL1.1	152.55	78.08	1933.21
Base (S2)	152.55	72.08	1955.21
CRU1.3 Ratio	0.072	0.042	0.886
CRU1.2 Ratio	0.071	0.039	0.890
CRU1.1 Ratio	0.071	0.036	0.893
Base Ratio	0.070	0.033	0.897

Table 7.15. Shapley Value and Ratio Changes with PRL and PRU in S2

	P2	PC	OC
PRLPRU1.3	197.55	72.08	1865.21
PRLPRU1.2	182.55	72.08	1895.21
PRLPRU1.1	167.55	72.08	1925.21
Base (S2)	152.55	72.08	1955.21
CRU1.3 Ratio	0.093	0.034	0.874
CRU1.2 Ratio	0.085	0.034	0.882
CRU1.1 Ratio	0.077	0.033	0.889
Base Ratio	0.070	0.033	0.897

It seems the impacts of lower and upper bound rates are linear on the players' Shapley values and are uncorrelated in the ECC. If the Canal operator could increase its rate more than the increased cost due to the expansion, the PC will have improved profit allocation in the ECC after the expansion is finished.

7.3. Conclusions of Following Games

Two small coalitions are analyzed and both have stable Shapley value solutions. Compared with the two small coalitions, the grand coalition has the highest total profit and offers the OC the highest profit allocation. However, all the other players get better profits in their small coalition than in the grand coalition. Comparing the two small coalitions, the OC prefers the East Coast Coalition {OC, P2, PC} because it offers a higher profit than the West Coast Coalition {OC, P1, R}.

Using the ECC to illustrate, the Shapley values allocate the benefits of cooperation to each player in the coalition {OC, P2, PC}. The allocation is efficient because the sum of benefit to each player is equal to the total benefit of the coalition. Because the Shapley value solution for the small coalitions is in the core, the allocation is also stable. LC and MMC provide very similar results to the Shapley Value.

Sensitivity analysis is conducted. A player's cost reduction has benefit to the whole coalition, but all the benefit is allocated to the player itself. The cost in some way reflects a player's absolute attribution to a coalition. On the other hand, the player's upper bound rate affects its relative market power to the OC. It has no impact on the coalition's value, and only changes the allocation difference between the player and the OC. Simultaneous changes of the PC's upper and lower bound rates are tested, as well as P2's upper and lower bound rates. It seems the impacts of lower and upper bound rates are linear and are not correlated in the small coalition.

The cost and rate changes' impact on players' profit values and ratios is very different from the grand coalition analysis in Chapter 6. The grand coalition has more complicated competition-cooperation relationships within its members. In contrast, the ECC has only three players and no competition exists among them. When more players are involved and more shipping chains and routes are available, the market becomes more complex and prediction of corporation/competition results could not be easily made intuitively. Using game theory to analyze the situation becomes more necessary for those situations. And, as shown by this case study, the Shapley value, LC, and MMC all have successfully analyzed the interacting relationship.

The last conclusion regards the Panama Canal expansion effect. In the ECC, the PC will not get a better profit if holding the Canal rate's upper bound and lower bound constant. If, as expected, the Panama Canal operator will increase its rate more than the increased cost after the expansion, the PC will have improved profit allocation in the ECC after the expansion is finished.

8. SUMMARY AND CONCLUSIONS

8.1. Summary of the Problem

The container shipping market is confronted with many challenges and has caught wide attention of many researchers. In addition to uncertainties and congestion problems, the complicated interacting relationships between the various agents are continuously changing and have important and direct impact on the shipment routes, volume, and prices. Different stakeholders along the shipment chain have different, very often conflicting, economic goals and may have cooperation or competition relationships. Their different market power impacts the negotiation process and how the profits/cost savings are divided.

One type of existing approaches to cargo spatial distribution problems uses optimization modeling and usually ignores the impact of stakeholders interactions. Another type either implicitly models the competition equilibrium of carriers and shippers, like Network Equilibrium Models, or explicity evaluates some types of non-cooperative strategies or cooperative solutions in the system. It is noticed that more comprehensive applications of non-cooperative game theory and some types of cooperative game approaches on the freight network planning problems began to merge. Some of those also used multi-level programming programs to examine the hierarchy relationships. But the applications are rare and apparently at an early stage.

In this dissertation, the cooperative game theory is utilized to solve the U.S. containerized import shipment optimization problem, and to investigate the relationships between the players. Bi-level optimization models are built to capture the hierarchy structure of the ocean shipping industry. Different types of coalitions and competition-cooperation schemes for the main players are assumed and solved using different bi-level models. The model results are input into cooperative game solutions. The Shapley value, the core, Least core, and Minmax core are calculated to understand, predict, and interpret the player relationships, optimal shipment routes, and strategic operational decisions in complex multi-agent container shipping systems.

8.2. Summary of Model Results

A case study with only five players is used to illustrate model results and coalition formations. Four scenarios are conducted and the model results indicate, if the grand coalition of the five players is to form, the OC will ship all or most (depending on if there is enough capacity) via the WCR before the Canal expansion. After the expansion is finished and both routes are served by the 8,000-TEU vessel, the OC will prefer the ECR.

The grand coalition in Chapter 6 is found as unstable; and the core does not exist for some scenarios. Two small coalitions are analyzed in Chapter 7 and both have stable Shapley value solutions. Compared with the two small coalitions, the grand coalition has the highest total profit and offers the OC the highest profit allocation. However, all the other players get better profits in their small coalition than in the grand coalition. Comparing the two small coalitions, the OC prefers the East Coast Coalition {OC, P2, PC} because it offers a higher profit than the West Coast Coalition {OC, P1, R}.

Sensitivity analyses are conducted for both the grand coalition game and the ECC game. The grand coalition game has five players belonging to two competing shipment chains, while the ECC game has only three players and no competition relationship exists. As expected, the influence of the parameter values' changes is easier to observe in the ECC game than in the grand coalition. In general, if a player could reduce its cost, it will earn additional market power in the coalition and a higher profit allocation. In the ECC, where no competition relationship exists among the members, the increase of its profit is equal to the reduction of its cost. However, in the grand coalition where the inter-relationship is more complicated, a player's profit increase is less than its cost reduction; and some benefit is allocated to the OC or other players. On the other hand, a player's upper bound rate is the highest rate that it could charge in a non-cooperative market, and affects its relative market power in relation to its coalition members.

Sensitivity analysis on the average cargo value in grand coalition proves that the quicker route is preferred for higher-valued cargoes, as more pipeline inventory cost is saved, ceteris paribus. In the grand coalition, the ECR players (P2 and PC) both benefit from the Canal expansion in terms of both Shapley value and unit profit even when the Canal's rate range is assumed unchanged. However, when there is capacity constraint at the East Coast terminal, EC players' Shapley values increase due to the expansion, but their unit profits actually decrease. In the ECC, the PC will not get a better profit if holding the Canal rate's upper bound and lower bound constant. All the benefit to the coalition due to the Panama Canal expansion is gained by the OC. If, as expected, the Panama Canal operator will increase its rate more than the increased cost after the expansion, the PC will have improved profit allocation in the ECC after the expansion is finished.

8.3. Implications

The different solution results of the 15 different bi-level models are a clear indication that, with different cooperation schemes, the OC will have different route choices and rate payments to other players. Ignoring the relationships of multiple entities fails to understand the real container shipping market.

The finding that the grand coalition for the case study is very unstable is mainly because there are two competing routes for one OC. That will not be necessarily true if more players are added to the game. And actually, by changing some parameter values, the grand coalition for this case study might have an un-empty core. Similarly, although the ECC is preferred by P2 and PC for this case study, the result may change if the parameter values and number of players in the game are changed. For each new case, the models have to be re-built and computed and solutions have to be re-calculated.

Based on the case study, the Panama Canal's expansion clearly has a positive impact on the relative market power of the ECR and a negative impact on the WCR when there is no capacity constraint problem. The Canal expansion has a two-sided impact on the OC in that it may save vessel operating costs for the OC, and may also hurt the OC's relative market power and final profit allocation.

Most of the findings are consistent with real world practice and expectations. Some results that are tricky to explain further prove that the shipping market is complicated and many factors are having an effect at the same time. When many players are involved in the market, player relationships will become more complicated, and the corporation and competition results could hardly be predicted intuitively. The cooperative game solutions offer a measurable tool to understand the interactive relationships in the ocean shipping industry, to compare the relative powers of players, and to make predictions of market equilibrium.

8.4. Contributions

The research contributes to the literature in a number of aspects.

1. Compared with studies that ignore player relationships, this dissertation incorporates four types of players in the U.S. containerized import market to analyze the optimal container shipment problem using cooperative game theory approaches. In contrast to some studies that focused on interactions of one or two types of players, the four types of players in this study are from different levels of the shipment chain, and their relationships are much more complicated than relationships among the same-level players. Different

solution approaches, including the core, Shapley value, Least core, and Minmax core, are used. From the extensive literature review, there are almost no studies of this type.

2. The hierarchy structure between the OC and the other players is captured by Bi-level Programming Problems (BLPP). In all, 16 bi-level models are built and calculated and 32 coalitions are analyzed for the case study. Following games are also added after the grand coalition is considered unstable.
3. While the Panama Canal expansion has been discussed vastly by scholars, no studies have quantitatively evaluated its impact on the container flow pattern or the market power of the different stakeholders in the container shipping market. This study shows that by comparing the before and after scenarios, the Panama Canal expansion's impact on the market could be directly investigated. By varying assumptions on terminal capacity constraints and other parameter values, insights on how the players interact with each other have also been gained.

8.5. Limitations, Challenges and Suggestions for Future Research

The five-player case study suffices for the purpose of demonstrating how the bi-level models are built and computed, and how the cooperative game solutions are calculated and interpreted for the U.S. container import market. But it is not sufficient to get a thorough picture of the market status, or even predict future market equilibrium. Similarly, a complete understanding of the Panama Canal's expansion and capacity constraint impact could not be obtained at this point.

In order to achieve that goal, more players need to be added to include nationwide containerized-import shipments. However, to include just 10 major U.S. ports, two origins (Asia and Europe), 48 contiguous states as the inland destinations, and five shipping companies, there will be at least 10 port operators, four U.S. railroad operators (BNSF, CSX, NS, CN), one trucking operator (assuming there is no competition among all trucking companies), two canal operators (Panama Canal and Suez Canal), and five OCs. With 22 players, the total number of possible coalitions will be 4,194,304 (2^{22}). For a simplier version with only five port operators, one railroad operator, one trucking operator, two canal operators, and three ocean carriers, there will still be 2,048 (2^{11}) coalition combinations. One solution to the large number of coalitions is to eliminate some "unrealistic" coalitions in the beginning. For example, assume there is no cooperation between the ports. When capacity constraints at some nodes or links are further assumed, the problem will become more intricate. The number of mathematical models and the complexity of each model will both rise dramatically. It is a challenge to model such a complex system using cooperative game theory approach.

Fixed demand is assumed in the dissertation, and the shippers' role is not considered. To have a demand function instead of the fixed value, the shippers' interaction with the OC could be analyzed. But the model will become hard to solve and the global solution algorithm has to be established. Trucking companies are not considred in the case study; and the demand destination is purposely selected to be very near Terminal 2. If a more interior destination is used instead, an inland carrier for the ECR has to be added, which will affect the power structure of the market.

Another important player that has been neglected in this study is the Suez Canal, due to the time limitation. A shift in trade lanes is underway already as some big shipping companies (e.g., Maersk Lines) are already transpassing via the Suez Canal instead of the Panama Canal for the Asia to East Coast routes. As the Panama Canal expansion is not finished yet, carriers have found that using large PostPanamax vessels on the Suez route to the East Coast is more profitable than through the Panama Canal. Adding the Suez Canal as another player is expected to change the power structure of the players, especially for the Panama Canal.

The Shapley value calculation is computatively extensive. As shown by this study, the LC and MMC provide very similar results to the Shapley Value, and have the advantages of much easier computation requirements and seeking fairness. For future research on a more complicated game, these two could be used instead of the Shapley value.

REFERENCES

Adamidou, Evdokia A. , and Alain L. Kornhauser. 1993. "A Game Theoretic/Network Equilibrium Solution Approach For The Railroad Freight Car Management Problem." *Transportation Research Part B* no. 27 (3):237-252.

Adler, Nicole. 2001. "Competition in a Deregulated Air Transportation Market." *European Journal of Operational Research* no. 129:337-345.

Al-Khayal, Faiz A., Reiner Horst, and Panos M. Pardalos. 1992. "Global Optimization of Concave Functions Subject to Quadratic Constraints: An Application in Nonlinear Bilevel Programming." *Annals of Operations Research* no. 34 (1):125-147.

Álvarez-SanJaime, Óscar, Pedro Cantos-Sánchez, Rafael Moner-Colonques, and José J. Sempere-Monerris. 2013. "Vertical Integration and Exclusivities in Maritime Freight Transport." *Transportation Research Part E* no. 51:50-61.

Anandalingam, G., and K. Nam. 1997. "Conflict and Cooperation in Designing International Telecommunication Networks." *Journal of the Operational Research Society* no. 48:600-611.

Army Corps of Engineers. 2007. USACE Aggregate Vessel Operating Cost Model. Maritime Strategies International, Ltd. and The Institute for Water Resources, US Army Corps of Engineers.

Arshinder, Arun Kanda, and S. G. Deshmukh. 2008. "Supply Chain Coordination: Perspectives, Empirical Studies And Research Directions." *International Journal of Production Economics* no. 115 (2):316-335.

Asgari, Nasrin, Reza Zanjirani Farahani, and Mark Goh. 2013. "Network Design Approach for Hub Ports-Shipping Companies Competition and Cooperation." *Transportation Research Part A* no. 48:1-18.

Audy, J. F., S. D'Amours, and L. M. Rousseau. 2011. "Cost Allocation in the Establishment of a Collaborative Transportation Agreement—An Application in the Furniture Industry." *Journal of the Operational Research Society* no. 62:960-970.

Aumann, R. J. 1959. "Acceptable Points in General Cooperative N-Person Games." In *Contributions to the Theory of Games IV*, edited by A.W. Tucker and R.D. Luce, 287-324. Princeton, NJ: Princeton University Press.

Aumann, R.J., and L.S. Shapley. 1974. *Values of Non-Atomic Games*. Princeton, NJ.: Princeton University Press.

Bahn, O., A. Haurie, S. Kypreos, and J.-P. Vial. 1998. "Advanced Mathematical Programming Modeling to Assess the Beneits of International CO2 Abatement Cooperation." *Environmental Modeling and Assessment* no. 3 (1/2):107-116.

Bard, Jonathan F. 1988. "Convex Two-Level Optimization." *Mathematical Programming* no. 40:15-27.

Bard, Jonathan F., and James Falk. 1982. "An Explicit Solution to the Multi-Level Programming Problem." *Computers and Operations Research* no. 9:77-100.

Bard, Jonathan F., and James T. Moore. 1990. "A Branch and Bound Algorithm for the Bilevel Programming Problem." *SIAM Journal on Scientific and Statistical Computing* no. 11 (2):281-292.

Bartholdi, John J. III, and Eda Kemahlioglu-Ziya. 2004. "Using Shapley Value To Allocate Saving in a Supply Chain." In *Supply Chain Optimization*, edited by Joseph Geunes and Panos M. Pardalos. Kluwer Optimization Series.

Bianco, Lucio, Massimiliano Caramia, and Stefano Giordani. 2009. "A Bilevel Flow Model for Hazmat Transportation Network Design." *Transportation Research Part C* no. 17:175-196.

Bloomberg L. P. 2013a. Data on Daily Hire Rates for Ocean Freight from Japan-South Korea to US-Can North Pacific 7/13/2005 to 8/1/2013. Retrieved September 3, 2013 from Bloomberg terminal.

Bloomberg L. P. 2013b. Data series on 380cst and MDO at Port of Los Angeles from 7/31/2000 to 7/29/2013. Retrived September 3, 2013 from Bloomberg terminal.

Bonney, Joseph. 2012. ILA, USMX Resume Contract Talks. http://www.joc.com/port-news/longshoreman-labor/ila-usmx-resume-contract-talks_20120628.html.

Bonney, Joseph. 2013. ILA, Employers Resume Local Bargaining. http://www.joc.com/port-news/longshoreman-labor/international-longshoremen%E2%80%99s-association/ila-employers-resume-local-bargaining_20130204.html.

Bracken, Jerome, and James T. McGill. 1973. "Mathematical Programs with Optimization Problems in the Constraints." *Operations Research* no. 21:37-44.

Bracken, Jerome, and James T. McGill. 1974. "Defense Applications of Mathematical Programs with Optimization Problems in the Constraints." *Operations Research* no. 22:1086-1096.

Bracken, Jerome, and James T. McGill. 1978. "Production and Marketing Decisions with Multiple Objectives in a Competitive Environment." *Journal of Optimization Theory and Applications* no. 24:449-458.

Brooks, Mary. 1993. "International Competitiveness-Assessing and Exploring Competitive Advantage by Ocean Container Carriers." *Logistics and Transportation Review* no. 29 (3):278-293.

Cachon, Gerard P., and Martin A. Lariviere. 1999. "Capacity Allocation Using Past Sales: When to Turn and Earn." *Management Science* no. 45:685-703.

Cachon, Gerard P., and Martin A. Lariviere. 2005. "Supply Chain Coordination with Revenue-Sharing Contracts: Strengths and Limitations." *Management Science* no. 51 (1):30-44.

Cachon, Gerard P., and Serguei Netessine. 2004. "Game Theory in Supply Chain Analysis." In *Supply Chain Analysis in the eBusiness Era*, edited by David Simchi-Levi, S. David Wu and Zuo-Jun Shen. Kluwer.

Candler, W., and R. Norton. 1977. *Multilevel Programming, Technical Report 20*. Washington D.C., USA: World Bank Development Research Center.

Castelli, Lorenzo, Giovanni Longo, Raffaele Pesenti, and Walter Ukovich. 2004. "Two-Player Noncooperative Games Over a Freight Transportation Network." *Transportation Science* no. 38 (2):149-159.

Chapman, Dan. 2012. Ports to Spend Big for Global Bounty. http://www.ajc.com/news/news/local/ports-to-spend-big-for-global-bounty/nQWWX/.

Chen, Rachel R., and Shuya Yin. 2010. "The Equivalence of Uniform and Shapley Value-Based Cost Allocations in a Specific Game." *Operations Research Letters* no. 38:539-544.

Colson, Benoît, Patrice Marcotte, and Gilles Savard. 2007. "An Overview of Bilevel Optimization." *Annals Operations Research* no. 153:235-256.

Cruijssen, Frans, Peter Borm, Hein Fleuren, and Herbert Hamers. 2010. "Supplier-Initiated Outsourcing: A Methodology to Exploit Synergy in Transportation." *European Journal of Operational Research* no. 207:763-774.

Drechsel, J., and A. Kimms. 2010. "Computing core Allocations Incooperative Games with an Application to Cooperative Procurement." *International Journal of Production Economics* no. 128:310-321.

Drechsel, J., and A. Kimms. 2011. "Cooperative Lot Sizing with Transshipments and Scarce Capacities: Solutions and Fair Cost Allocations." *International Journal of Production Research* no. 49 (9):2643-2668.

Edmunds, Thomas A., and Jonathan F. Bard. 1991. "Algorithms for Nonlinear Bilevel Mathematical Programs." *IEEE Transactions on Systems, Man, and Cybernetics* no. 21 (1):83-89.

Edmunds, Thomas A., and Jonathan F. Bard. 1992. "An Algorithm for the Mixed-Integer Nonlinear Bilevel Programming Problem." *Annals of Operations Research* no. 34:149-162.

Fan, Lei. 2010. *Optimization Model and Risk Analysis for Global Supply Chain in Container Shipments: Imports to the United States*. PhD Dissertation, Transportation and Logistics, North Dakota State University.

Fan, Lei, William Wilson, and Bruce Dahl. 2012. "Congestion, Port Expansion and Spatial Competition for Us Container Imports." *Transportation Research Part E* no. 48 (6):1121-1136.

Fan, Lei, William Wilson, and Denver Tolliver. 2010. "Optimal Network Flows for Containerized Imports to the United States." *Transportation Research Part E* no. 46 (5):735-749.

Fatima, Shaheen S., Michael Wooldridge, and Nicholas R. Jennings. 2008. "A Linear Approximation Method for the Shapley Value." *Artificial Intelligence* no. 172:1673-1699.

Filar, J. A., and P. S. Gaertner. 1997. "A Regional Allocation of World CO2 Emission Reductions." *Mathematics and Computers in Simulation* no. 43:269-275.

Ford, Eric W., Rebecca Wells, and Barbara Bailey. 2004. "Sustainable Network Advantages: A Game Theoretic Approach to Community-Based Health Care Coalitions." *Health Care Management Review* no. 29:159-169.

Fortuny-Amat, José, and Bruce McCarl. 1981. "A Representation and Economic Interpretation of a Two-Level Programming Problem." *The Journal of the Operational Research Society* no. 32 (9):783-792.

Franc, Pierre, and Martijin Van der Horst. 2010. "Understanding Hinterland Service Integration by Shipping Lines and Terminal Operators: A Theoretical And Empirical Analysis." *Journal of Transport Geography* no. 18 (4):557-566.

Frisk, M., M. Göthe-Lundgren, K. Jörnsten, and M. Rönnqvist. 2010. "Cost Allocation in Collaborative Forest Transportation." *European Journal of Operational Research* no. 205:448-458.

Fusillo, Michael. 2006. "Some Notes on Structure and Stability in Liner Shipping." *Maritime Policy and Management* no. 33 (5):463-475.

Gillies, D. B. 1959. *Solutions to General Non-Zero-Sum Games*.

Hackett, Ben. 2003. "National Dredging Needs Study of U.S. Ports and Harbors: Update 2000." *DRI-WEFA*.

Hansen, Pierre, Brigitte Jaumard, and Gilles Savard. 1992. "New Branch-and-Bound Rules for Linear Bilevel Programming." *SIAM Journal of Scientific and Statistical Computing* no. 13:1194-1217.

Harker, Patrick T., and Terry L. Friesz. 1986a. "Prediction of Intercity Freight Flows, I: Theory." *Transportation Research Part B* no. 20 (2):139-153.

Harker, Patrick T., and Terry L. Friesz. 1986b. "Prediction of Intercity Freight Flows, II: Mathematical Formulation." *Transportation Research Part B* no. 20 (2):155-174.

Hayuth, Yehuda. 1987. *Intermodality: Concept and Practice*. London: Lloyds of London Press.

Holeywell, Ryan. 2012. Panama Canal Expansion Has U.S. Ports Rushing: States are seeking to spend billions of dollars to build bigger ports to accommodate the massive ships that will soon be traveling through the canal. Can they move quickly enough? , http://www.governing.com/panama-canal-expansion-has-ports-rushing.html.

Hong, Sungwook, and Patrick T. Harker. 1992. "Air Traffic Network Equilibrium: Toward Frequency, Price and Slot Priority Analysis." *Transportation Research Part B* no. 26 (4):307-323.

Huang, Yun, George Q. Huang, and Stephen T. Newman. 2011. "Coordinating Pricing and Inventory Decisions in a Multi-Level Supply Chain: A Game-Theoretic Approach." *Transportation Research Part E* no. 47:115-129.

Hurley, W. J., and E. R. Petersen. 1994. "Nonlinear Tariffs and Freight Network Equilibrium." *Transportation Science* no. 28 (3):236-245.

Ishii, Masahiro, Paul Tae-Woo Lee, Koichiro Tezuka, and Young-Tae Chang. 2013. "A Game Theoretical Analysis of Port Competition." *Transportation Research Part E* no. 49 (1):92-106.

Journal of Commerce. 2013a. CMA CGM, Maersk Line and MSC to Partner on East-West Trades. http://www.joc.com/maritime-news/container-lines/p3-network/cma-cgm-maersk-line-and-msc-partner-east-west-trades_20130618.html.

Journal of Commerce. 2013b. East-West US Intermodal Rates Fall to Eight-Week Low. http://www.joc.com/rail-intermodal/intermodal-shipping/east-west-us-intermodal-rates-fall-eight-week-low_20130814.html.

Journal of Commerce. 2013c. SCFI Shanghai-to-US Spot Rates Show Further GRI Erosion. http://www.joc.com/maritime-news/trade-lanes/trans-pacific/scfi-shanghai-us-spot-rates-show-further-gri-erosion_20130816.html.

Journal of Commerce. 2013d. US Intermodal Rates Slip Despite Higher Diesel Prices. http://www.joc.com/rail-intermodal/intermodal-shipping/us-intermodal-rates-slip-despite-higher-diesel-prices_20130514.html.

Jula, Payman, and Robert C. Leachman. 2011a. "Long- and Short-Run Supply chain optimization models for the allocation and congestion management of containerized imports from Asia to the United States." *Transportation Research Part E* no. 47 (5):593-608.

Jula, Payman, and Robert C. Leachman. 2011b. "A Supply-Chain Optimization Model of the Allocation of Containerized Imports from Asia to the United States." *Transportation Research Part E* no. 47:609-622.

Kolstad, Charles D. 1985. "A Review of the Literature on Bi-Level Mathematical Programming " In *Technical Report LA-10284-MS*. Los Alamos, New Mexico, USA: Los Alamos National Laboratory.

Krajewska, M.A., H. Kopfer, G. Laporte, S. Ropke, and G Zaccour. 2008. "Horizontal Cooperation among Freight Carriers: Request Allocation and Profit Sharing." *Journal of the Operational Research Society,* no. 59 (11):1483-1491.

Le-Griffin, H. D., and M. Murphy. 2006. Container Terminal Productivity: Experiences at Ports of Los Angeles and Long Beach. University of Southern California.

Leachman, Robert. 2010. Final Report-Port and Modal Elasticity Study, Phase II. Leachman & Associates LLC.

Lee, Hyangsook, Maria Boileb, Sotirios Theofanisc, and Sangho Chooa. 2012. "Modeling the Oligopolistic and Competitive Behavior of Carriers in Maritime Freight Transportation Networks." *Procedia - Social and Behavioral Sciences* no. 54:1080-1094.

Levine, Brian, Linda Nozick, and Dean Jones. 2009. "Estimating an Origin–Destination Table for US Imports of Waterborne Containerized Freight." *Transportation Research Part E* no. 45 (4):611-626.

Lin, Cheng-Chang, and Chao-Chen Hsieh. 2012. A Cooperative Coalitional Game in Duopolistic Supply-Chain Competition. *Networks and Spatial Economics* 12: 129-146, http://dx.doi.org/10.1007/s11067-011-9154-y.

Liu, Peng, Yaohua Wu, and Na Xu. 2010. "Allocating Collaborative Profit in Less-than-Truckload Carrier Alliance." *Journal of Service Science and Management* no. 3:143-149.

Lozano, S., P. Moreno, B. Adenso-Díaz, and E. Algaba. 2013. "Cooperative Game Theory Approach to Allocating Benefits Of Horizontal Cooperation." *European Journal of Operational Research*. doi: http://dx.doi.org/10.1016/j.ejor.2013.02.034.

Magala, Mateus, and Adrian Sammons. 2008. "A New Approach to Port Choice Modelling." *Maritime Economics and Logistics* no. 10:9-34.

Maschler, M., B. Peleg, and L.S. Shapley. 1979. "Geometric Properties of the Kernel, Nucleolus, and Related Solution Concepts." *Mathematics of Operations Research* no. 4:303-338.

Mercator Transport Group. 2005. Forecast of Container Vessel Specifications and Port Calls Within San Pedro Bay. Mercator Transport Group, Bellevue, WA.

Moreno-Quintero, Eric, Tony Fowkes, and David Watling. 2013. "Modelling Planner–Carrier Interactions in Road Freight Transport: Optimisation of Road Maintenance Costs via Overloading Control." *Transportation Research Part E* no. 50:68-83.

Myerson, Roger B. 1991. *Game Theory: Analysis of Conflict*: Harvard University Press.

Nagarajan, Mahesh, and Greys Sosic. 2008. "Game-Theoretic Analysis of Cooperation among Supply Chain Agents: Review and Extensions." *European Journal of Operational Research* no. 187:719-745.

Notteboom, Theo E. 2004. "Container Shipping and Ports: An Overview." *Review of Network Economics* no. 3 (2):86-106.

Notteboom, Theo E. 2007. "Strategic Challenges to Container Ports in a Changing Market Environment." *Research in Transportation Economics* no. 17 (29-52).

Nouweland, A. van den, P. Borm, W. van Golstein Brouwers, R. Groot Bruinderink, and S. Tijs. 1996. "A Game Theoretic Approach to Problems in Telecommunication." *Management Science* no. 42:294-303.

Özener, Okan Orsan, and Ozlem Ergun. 2008. "Allocating Costs in a Collaborative Transportation Procurement Network." *Transportation Science* no. 42 (2):146-165.

Panama Canal Authority. 2006. Proposal for the Expansion of the Panama Canal: Third Set of Locks Project. http://www.panCanal.com/eng/plan/documentos/propuesta/acp-expansion-proposal.pdf.

Panama Canal Authority. 2010. The New Panama Canal: A better way to go. http://www.panCanal.com/eng/plan/documentos/propuesta/acp-panama-Canal-an-overview.pdf.

Panayides, Photis M., and Robert Wiedmer. 2011. "Strategic Alliances in Container Liner Shipping." *Research in Transportation Economics* no. 32:25-38.

Park, Kyunghee. 2013. Maersk Line to Dump Panama Canal for Suez as Ships Get Bigger. http://www.bloomberg.com/news/2013-03-11/maersk-line-to-dump-panama-canal-for-suez-as-ships-get-bigger.html.

Petrosjan, Leon, and Georges Zaccour. 2003. "Time-Consistent Shapley Value Allocation of Pollution Cost Reduction." *Journal of Economic Dynamics & Control* no. 27:381-398.

Pirrong, Stephen C. 1992. "An Application of the core Theory to the Analysis of Ocean Shipping Markets." *Journal of Law and Economics* no. 35:89-131.

Rosenthal, Edward C. 2008. "A Game-Theoretic Approach to Transfer Pricing in a Vertically Integrated Supply Chain." *International Journal of Production Economics* no. 115:542-552.

Saeed, Naima, and Odd I. Larsen. 2010. "An Application of Cooperative Game Among Container Terminals of One Port." *European Journal of Operational Research* no. 203:393-403.

Samuelson, Paul A. . 1952. "Spatial Price Equilibrium and Linear Programming." *American Economic Review* no. 42 (3):283-303.

Sayman, Serdar, Stephen J. Hoch, and Jagmohan S. Raju. 2002. "Positioning of Store Brands." *Marketing Science* no. 21 (4):378-397.

Segall, R. S. 1990. "Using Branch-and-Bound to Solve Bi-Level Geometric Programming Problems: A New Optimization Model." *Applied Mathematical Modeling* no. 14 (5):271-274.

Shapley, L. S. 1953. "A Value for N-Person Games " In *Contributions to the Theory of Games II. Annals of Mathematical Studies 28*, edited by H.W. Kuhn and A.W. Tucker. Princeton, NJ.: Princeton University Press.

Shapley, L. S. 1971. "cores of Convex Games." *International Journal of Game Theory* no. 1:11-26.

Shapley, L. S., and M. Shubik. 1966. "Quasi-cores in a Monetary Economy with Nonconvex Preferences." *Econometrica* no. 34 (4):805-827.

Sheffi, Yosef. 1985. *Urban Transportation Networks: Equilibrium Analysis with Mathematical Programming Methods*. Englewood Cliffs, NJ: Prentice-Hall.

Shepherd, William G. 1970. *Market Power and Economic Welfare*: New York: Random House.

Sherali, Hanif D., and Brian J. Lunday. 2011. "Equitable Apportionment of Railcars within A Pooling Agreement for Shipping Automobiles." *Transportation Research Part E* no. 47 (2):263-283.

Shiao, Guo-Chou, and Cherng-Chwan Hwang. 2013. "Analyzing Competition of International Air Cargo Carriers in the Asian General Air Cargo Markets." *Transport Policy* no. 27:164-170.

Silva, Marcelino Aurélio Vieira da, and Marcio de Almeida D'Agosto. 2013. "A Model to Estimate the Origin–Destination Matrix for Soybean Exportation in Brazil." *Journal of Transport Geography* no. 26:97-107.

Sinha, Surabhi, and S.B. Sinha. 2002. "KKT Transformation Approach for Multi-Objective Multi-Level Linear Programming Problems." *European Journal of Operational Research* no. 143:19-31.

Sjostrom, William. 1989. "Collusion in Ocean Shipping: A Test of Monopoly and Empty core Models." *Journal of Political Economy* no. 97:1160-1179.

Sjostrom, William. 1993. "Antitrust Immunity for Shipping Conferences: An Empty core Approach." *Antitrust Bulletin* no. 38:419-423.

Soppé, Martin, Francesco Parola, and Antoine Frémont. 2009. "Emerging Inter-Industry Partnerships Between Shipping Lines and Stevedores: From Rivalry to Cooperation?" *Journal of Transport Geography* no. 17:10-20.

Southworth, Frank, and Bruce Peterson. 2000. "Intermodal and International Freight Network Modeling." *Transportation Research Part C* no. 8:147-166.

Stackelberg, Heinrich von. 1934. *Marktform und Gleichgewicht*. Vienna: Julius Springer.

Talley, Wayne K., and ManWo Ng. 2013. "Maritime Transport Chain Choice by Carriers, Ports and Shippers." *International Journal of Production Economics* no. 142 (2):311-316.

Thomas, L.C. 1986. *Games, Theory and Applications*. Mineola, N.Y.: Dover Publications.

Tijs, S. H., and T.S.H. Driessen. 1986. "Game Theory and Cost Allocation Problems." *Management Science* no. 32 (8):1015-1028.

Tioga Group. 2007. Maritime Transportation System: Trends and Outlook. Institute for Water Resources.

U.S. Surface Transportation Board. 2011. Economic Data: Waybill.

UNCTAD. 2011. Review of Maritime Transport. United Nations Conference on Trade and Development, United Nations.

Vicente, L. N., G. Savard, and J. J. Júdice. 1996. "Discrete Linear Bilevel Programming Problem." *Journal of Optimization Theory and Applications* no. 89 (3):597-614.

Vicente, Luis N., and Paul H. Calamai. 1994. "Bilevel and Multilevel Programming: A Bibliography Review." *Journal of Global Optimization* no. 5:291-306.

von Neumann, John, and Oskar Morgenstern. 1944. *Theory of Games and Economic Behavior*. Second Ed., 1947 ed. Princeton: Princeton University Press.

Wang, Hongwei, Min Guo, and Janet Efstathiou. 2004. "A Game-Theoretic Cooperative Mechanism Design for a Two-Echelon Decentralized Supply Chain." *European Journal of Operational Research* no. 157 (2):372-388.

Wang, Ya. 2002. *A Bi-Level Programming Approach for the Shipper-Carrier Network Problem*. PhD Dissertation, Interdisciplinary Program in Transportation, New Jersey Institute of Technology.

Wie, Byung-Wook. 1995. "A Differential Game Approach to the Dynamic Mixed Behavior Traffic Network Equilibrium Problem." *European Journal of Operational Research* no. 83 (1):117-136.

Wilson, William W, Bruce Dahl, and Lei Fan. 2010. Towards a Global Forecast of Container Flows Container Model and Analysis: Longer Term Analysis of Infrastructure Demands and Risks. In *Task Report: Panama Canal Extension*.

Xiao, Feng, and Hai Yang. 2007. "Three-Player Game-Theoretic Model over a Freight Transport Network." *Transportation Research Part C* no. 15 (4):209-217.

Yang, Dong, Miaojia Liu, and Xiaoning Shi. 2011. "Verifying Liner Shipping Alliance's Stability by Applying core Theory." *Research in Transportation Economics* no. 32:15-24.

Yang, Xuejing, Joyce M.W. Low, and Loon Ching Tang. 2011. "Analysis of Intermodal Freight from China to Indian Ocean: A Goal Programming Approach." *Journal of Transport Geography* no. 19 (4):515-527.

Zhao, Yingxue, Shouyang Wang, T.C.E. Cheng, Xiaoqi Yang, and Zhimin Huang. 2010. "Coordination of Supply Chains by Option Contracts: A Cooperative Game Theory Approach." *European Journal of Operational Research* no. 207:668-675.

Zheng, Yingfei, Shuxia Zhang, Xiaojinga Chen, and Fang Liu. 2011. "Application of Modified Shapley Value in Gains Allocation of Closed-loop Supply Chain under Third-Party Reclaim." *Energy Procedia* no. 5:980-984.

APPENDIX A. LIST OF MODELS AND CONSTRAINTS

Table A. 1. Model List for Case Study

Model & Level	Coalition Value	Objective Function
M_0 Level 1	$v(\{OC\}) = v_0^1$	$\max(R_{oc} - C_{oc} - R_{p1} - R_{p2} - R_{pc} - R_r) = v_0^1$
M_0 Level 2	$v(\{R, P1, P2, PC\}) = v_0^2$	$\max(f_{p1} + f_{p2} + f_{pc} + f_r) = v_0^2$
M_1 Level 1	$v(\{OC, P1\}) = v_1^1$	$max(R_{oc} - C_{oc} - C_{p1} - R_{p2} - R_{pc} - R_r) = v_1^1$
M_1 Level2	$v(\{P2, PC, R\}) = v_1^2$	$max(f_{p2} + f_{pc} + f_r) = v_1^2$
M_2 Level 1	$v(\{OC, P2\}) = v_2^1$	$max(R_{oc} - C_{oc} - R_{p1} - C_{p2} - R_{pc} - R_r) = v_2^1$
M_2 Level 2	$v(\{P1, PC, R\}) = v_2^2$	$max(f_{p1} + f_{pc} + f_r) = v_2^2$
M_3 Level 1	$v(\{OC, PC\}) = v_3^1$	$max(R_{oc} - C_{oc} - R_{p1} - R_{p2} - C_{pc} - R_r) = v_3^1$
M_3 Level 2	$v(\{P1, P2, R\}) = v_3^2$	$max(f_{p2} + f_{p1} + f_r) = v_3^2$
M_4 Level 1	$v(\{OC, R\}) = v_4^1$	$max(R_{oc} - C_{oc} - R_{p1} - R_{p2} - R_{pc} - C_r) = v_4^1$
M_4 Level 2	$v(\{P2, PC, P1\}) = v_4^2$	$max(f_{p2} + f_{pc} + f_{p1}) = v_4^2$
M_5 Level 1	$v(\{OC, P1, P2\}) = v_5^1$	$max(R_{oc} - C_{oc} - C_{p1} - C_{p2} - R_{pc} - R_r) = v_5^1$
M_5 Level 2	$v(\{R, PC\}) = v_5^2$	$max(f_r + f_{pc}) = v_5^2$
M_6 Level 1	$v(\{OC, P1, PC\}) = v_6^1$	$max(R_{oc} - C_{oc} - C_{p1} - R_{p2} - C_{pc} - R_r) = v_6^1$
M_6 Level 2	$v(\{R, P2\}) = v_6^2$	$max(f_r + f_{p2}) = v_6^2$
M_7 Level 1	$v(\{OC, P1, R\}) = v_7^1$	$max(R_{oc} - C_{oc} - C_{p1} - R_{p2} - R_{pc} - C_r) = v_7^1$
M_7 Level 2	$v(\{P2, PC\}) = v_7^2$	$max(f_{pc} + f_{p2}) = v_7^2$
M_8 Level 1	$v(\{OC, PC, P2\}) = v_8^1$	$max(R_{oc} - C_{oc} - R_{p1} - C_{p2} - C_{pc} - R_r) = v_8^1$
M_8 Level 2	$v(\{R, P1\}) = v_8^2$	$max(f_r + f_{p1}) = v_8^2$
M_9 Level 1	$v(\{OC, R, P2\}) = v_9^1$	$max(R_{oc} - C_{oc} - R_{p1} - C_{p2} - R_{pc} - C_r) = v_9^1$
M_9 Level 2	$v(\{P1, PC\}) = v_9^2$	$max(f_{pc} + f_{p1}) = v_9^2$
M_{10} Level 1	$v(\{OC, R, PC\}) = v_{10}^1$	$max(R_{oc} - C_{oc} - R_{p1} - R_{p2} - C_{pc} - C_r) = v_{10}^1$
M_{10} Level 2	$v(\{P1, P2\}) = v_{10}^2$	$max(f_{p2} + f_{p1}) = v_{10}^2$
M_{11} Level 1	$v(\{OC, P1, P2, PC\}) = v_{11}^1$	$max(R_{oc} - C_{oc} - C_{p1} - C_{p2} - C_{pc} - R_r) = v_{11}^1$
M_{11} Level 2	$v(\{R\}) = v_{11}^2$	$max(f_r) = v_{11}^2$
M_{12} Level 1	$v(\{OC, R, P2, P1\}) = v_{12}^1$	$max(R_{oc} - C_{oc} - C_{p1} - C_{p2} - R_{pc} - C_r) = v_{12}^1$
M_{12} Level 2	$v(\{PC\}) = v_{12}^2$	$max(f_{pc}) = v_{12}^2$
M_{13} Level 1	$v(\{OC, R, PC, P1\}) = v_{13}^1$	$max(R_{oc} - C_{oc} - C_{p1} - R_{p2} - C_{pc} - C_r) = v_{13}^1$
M_{13} Level 2	$v(\{P2\}) = v_{13}^2$	$max(f_{p2}) = v_{13}^2$
M_{14} Level 1	$v(\{OC, R, P2, PC\}) = v_{14}^1$	$max(R_{oc} - C_{oc} - R_{p1} - C_{p2} - C_{pc} - C_r) = v_{14}^1$
M_{14} Level 2	$v(\{P1\}) = v_{14}^2$	$max(f_{p1}) = v_{14}^2$
M_{15} Level 1	$v(\{OC, R, P1, P2, PC\}) = v_{15}^1$	$max(R_{oc} - C_{oc} - C_{p1} - C_{p2} - C_{pc} - C_r) = v_{15}^1$
M_{15} Level 2	$v(\{\emptyset\}) = v_{15}^2 = 0$	$max(\emptyset) = v_{15}^2$

Table A. 2. Constraint Sets

Model	Original Constraints	Constraints after KKT Transformation	
M_0	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $PRL_2 \le pr_2 \le PRU_2$ $RRL \le rr \le RRU$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $PRL_2 \le pr_2 \le PRU_2$ $RRL \le rr \le RRU$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$ $feu_1 - u_1 + u_5 = 0$ $feu_2 - u_2 + u_6 = 0$	$feu_1 - u_3 + u_7 = 0$ $feu_2 - u_4 + u_8 = 0$ $u_1 * (PRU_1 - pr_1) = 0$ $u_2 * (PRU_2 - pr_2) = 0$ $u_3 * (RRU - rr) = 0$ $u_4 * (CRU - cr) = 0$ $u_5 * (PRL_1 - pr_1) = 0$ $u_6 * (PRL_2 - pr_2) = 0$ $u_7 * (RRL - rr) = 0$ $u_8 * (CRL - cr) = 0$
M_1	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_2 \le pr_2 \le PRU_2$ $RRL \le rr \le RRU$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_2 \le pr_2 \le PRU_2$ $RRL \le rr \le RRU$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$ $feu_2 - u_2 + u_6 = 0$	$feu_1 - u_3 + u_7 = 0$ $feu_2 - u_4 + u_8 = 0$ $u_2 * (PRU_2 - pr_2) = 0$ $u_3 * (RRU - rr) = 0$ $u_4 * (CRU - cr) = 0$ $u_6 * (PRL_2 - pr_2) = 0$ $u_7 * (RRL - rr) = 0$ $u_8 * (CRL - cr) = 0$
M_2	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $RRL \le rr \le RRU$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $RRL \le rr \le RRU$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$ $feu_1 - u_1 + u_5 = 0$	$feu_1 - u_3 + u_7 = 0$ $feu_2 - u_4 + u_8 = 0$ $u_1 * (PRU_1 - pr_1) = 0$ $u_3 * (RRU - rr) = 0$ $u_4 * (CRU - cr) = 0$ $u_5 * (PRL_1 - pr_1) = 0$ $u_7 * (RRL - rr) = 0$ $u_8 * (CRL - cr) = 0$
M_3	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $PRL_2 \le pr_2 \le PRU_2$ $RRL \le rr \le RRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $PRL_2 \le pr_2 \le PRU_2$ $RRL \le rr \le RRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$ $feu_1 - u_1 + u_5 = 0$ $feu_2 - u_2 + u_6 = 0$	$feu_1 - u_3 + u_7 = 0$ $u_1 * (PRU_1 - pr_1) = 0$ $u_2 * (PRU_2 - pr_2) = 0$ $u_3 * (RRU - rr) = 0$ $u_5 * (PRL_1 - pr_1) = 0$ $u_6 * (PRL_2 - pr_2) = 0$ $u_7 * (RRL - rr) = 0$
M_4	$\sum_j(feu_j) = DMD$ $feu_j = Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $PRL_2 \le pr_2 \le PRU_2$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $PRL_2 \le pr_2 \le PRU_2$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$ $feu_1 - u_1 + u_5 = 0$ $feu_2 - u_2 + u_6 = 0$	$feu_2 - u_4 + u_8 = 0$ $u_1 * (PRU_1 - pr_1) = 0$ $u_2 * (PRU_2 - pr_2) = 0$ $u_4 * (CRU - cr) = 0$ $u_5 * (PRL_1 - pr_1) = 0$ $u_6 * (PRL_2 - pr_2) = 0$ $u_8 * (CRL - cr) = 0$
M_5	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $RRL \le rr \le RRU$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $RRL \le rr \le RRU$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$feu_1 - u_3 + u_7 = 0$ $feu_2 - u_4 + u_8 = 0$ $u_3 * (RRU - rr) = 0$ $u_4 * (CRU - cr) = 0$ $u_7 * (RRL - rr) = 0$ $u_8 * (CRL - cr) = 0$

Table A.2. Constraint Sets (continued)

Model	Original Constraints	Constraints after KKT Transformation	
M_6	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_2 \le pr_2 \le PRU_2$ $RRL \le rr \le RRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_2 \le pr_2 \le PRU_2$ $RRL \le rr \le RRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$ $feu_2 - u_2 + u_6 = 0$	$feu_1 - u_3 + u_7 = 0$ $u_2 * (PRU_2 - pr_2) = 0$ $u_3 * (RRU - rr) = 0$ $u_6 * (PRL_2 - pr_2) = 0$ $u_7 * (RRL - rr) = 0$
M_7	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_2 \le pr_2 \le PRU_2$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_2 \le pr_2 \le PRU_2$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$ $feu_2 - u_2 + u_6 = 0$	$feu_2 - u_4 + u_8 = 0$ $u_2 * (PRU_2 - pr_2) = 0$ $u_4 * (CRU - cr) = 0$ $u_6 * (PRL_2 - pr_2) = 0$ $u_8 * (CRL - cr) = 0$
M_8	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $RRL \le rr \le RRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $RRL \le rr \le RRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$ $feu_1 - u_1 + u_5 = 0$	$feu_1 - u_3 + u_7 = 0$ $u_1 * (PRU_1 - pr_1) = 0$ $u_3 * (RRU - rr) = 0$ $u_5 * (PRL_1 - pr_1) = 0$ $u_7 * (RRL - rr) = 0$
M_9	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$ $feu_1 - u_1 + u_5 = 0$	$feu_2 - u_4 + u_8 = 0$ $u_1 * (PRU_1 - pr_1) = 0$ $u_4 * (CRU - cr) = 0$ $u_5 * (PRL_1 - pr_1) = 0$ $u_8 * (CRL - cr) = 0$
M_{10}	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $PRL_2 \le pr_2 \le PRU_2$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $PRL_2 \le pr_2 \le PRU_2$ $feu_j, pr_j, rr, cr, u_i \ge 0$ $feu_1 - u_1 + u_5 = 0$ $feu_2 - u_2 + u_6 = 0$	$u_1 * (PRU_1 - pr_1) = 0$ $u_2 * (PRU_2 - pr_2) = 0$ $u_5 * (PRL_1 - pr_1) = 0$ $u_6 * (PRL_2 - pr_2) = 0$
M_{12}	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $CRL \le cr \le CRU$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$feu_2 - u_4 + u_8 = 0$ $u_4 * (CRU - cr) = 0$ $u_8 * (CRL - cr) = 0$
M_{13}	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_2 \le pr_2 \le PRU_2$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_2 \le pr_2 \le PRU_2$ $feu_j, pr_j, rr, cr, u_i \ge 0$ $feu_2 - u_2 + u_6 = 0$	$u_2 * (PRU_2 - pr_2) = 0$ $u_6 * (PRL_2 - pr_2) = 0$
M_{14}	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $feu_j, pr_j, rr, cr, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $PRL_1 \le pr_1 \le PRU_1$ $feu_j, pr_j, rr, cr, u_i \ge 0$ $feu_1 - u_1 + u_5 = 0$	$u_1 * (PRU_1 - pr_1) = 0$ $u_5 * (PRL_1 - pr_1) = 0$
M_{15}	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $feu_j, u_i \ge 0$	$\sum_j(feu_j) = DMD$ $feu_j \le Cap(j)$ $feu_j, u_i \ge 0$	

APPENDIX B. MODEL RESULTS

Table B.1. S1 Results

Model	L1_Players	L1_Profit	L2_Profit	FEU_LA	FEU_NF	PR_LA	PR_NF	RR	PC
0	OC	109,840,000	13,440,000	0	64,000	225	300	1,617	220
1	OC P1	109,840,000	13,440,000	0	64,000	0	300	2,037	220
2	OC P2	119,840,000	3,840,000	0	64,000	225	0	1,620	220
3	OC PC	115,320,000	9,600,000	0	64,000	224	300	1,620	0
4	OC R	120,472,000	9,600,000	64,000	0	300	300	0	220
5	OC P1 P2	119,840,000	3,840,000	0	64,000	0	0	1,685	220
6	OC P1 Pc	115,320,000	9,600,000	0	64,000	0	300	1,623	0
7	OC P1 R	130,412,000	0	64,000	0	0	178	0	220
8	OC P2 PC	125,320,000	0	0	64,000	224	0	1,503	0
9	OC P2 R	120,472,000	9,600,000	64,000	0	300	0	0	203
10	OC PC R	120,472,000	9,600,000	64,000	0	300	191	0	0
11	OC P1 P2 PC	125,320,000	0	0	64,000	0	0	1,664	0
12	OC P1 P2 R	130,412,000	0	64,000	0	0	0	0	186
13	OC P1 PC R	130,412,000	0	64,000	0	0	300	0	0
14	OC P2 PC R	125,320,000	0	0	64,000	221	0	0	0
15	OC P1 P2 PC R	130,412,000	0	64,000	0	0	0	0	0

Table B.2. S2 Results

model	L1_Players	L1_Profit	L2_Profit	FEU_LA	FEU_Nk	PR_LA	PR_Nk	RR	PC
0	OC	124,200,000	13,440,000	0	64,000	225	300	1,618	220
1	OC P1	124,200,000	13,440,000	0	64,000	0	300	2,179	220
2	OC P2	134,120,000	3,840,000	0	64,000	225	0	1,405	220
3	OC PC	129,580,000	9,600,000	0	64,000	225	300	1,613	0
4	OC R	124,200,000	13,440,000	0	64,000	216	300	0	220
5	OC P1 P2	134,120,000	3,840,000	0	64,000	0	0	1,626	220
6	OC P1 Pc	129,580,000	9,600,000	0	64,000	0	300	1,619	0
7	OC P1 R	124,200,000	13,440,000	0	64,000	0	300	0	220
8	OC P2 PC	139,520,000	0	0	64,000	222	0	1,586	0
9	OC P2 R	134,120,000	3,840,000	0	64,000	300	0	0	220
10	OC PC R	129,580,000	9,600,000	0	64,000	234	300	0	0
11	OC P1 P2 PC	139,520,000	0	0	64,000	0	0	1,548	0
12	OC P1 P2 R	134,120,000	3,840,000	0	64,000	0	0	0	220
13	OC P1 PC R	129,580,000	9,600,000	0	64,000	0	300	0	0
14	OC P2 PC R	139,520,000	0	0	64,000	168	0	0	0
15	OC P1 P2 PC R	139,520,000	0	0	64,000	0	0	0	0

Table B.3. S3 Results

model	L1_Players	L1_Profit	L2_Profit	FEU_LA	FEU_Nk	PR_LA	PR_Nk	RR	PC
0	OC	96,286,400	29,657,600	12,800	51,200	300	300	2,280	220
1	OC P1	98,274,400	27,737,600	12,800	51,200	0	300	2,280	220
2	OC P2	104,286,400	21,977,600	12,800	51,200	300	0	2,280	220
3	OC PC	100,670,400	26,585,600	12,800	51,200	300	300	2,280	0
4	OC R	123,568,000	10,368,000	51,200	12,800	300	300	0	220
5	OC P1 P2	106,274,400	20,057,600	12,800	51,200	0	0	2,280	220
6	OC P1 Pc	102,658,400	24,665,600	12,800	51,200	0	300	2,280	0
7	OC P1 R	131,520,000	2,688,000	51,200	12,800	0	300	0	220
8	OC P2 PC	108,670,400	18,905,600	12,800	51,200	300	0	2,280	0
9	OC P2 R	125,568,000	8,448,000	51,200	12,800	300	0	0	220
10	OC PC R	124,664,000	9,600,000	51,200	12,800	300	300	0	0
11	OC P1 P2 PC	110,658,400	16,985,600	12,800	51,200	0	0	2,280	0
12	OC P1 P2 R	133,520,000	768,000	51,200	12,800	0	0	0	220
13	OC P1 PC R	132,616,000	1,920,000	51,200	12,800	0	300	0	0
14	OC P2 PC R	124,350,400	1,920,000	12,800	51,200	300	0	0	0
15	OC P1 P2 PC R	134,616,000	0	51,200	12,800	0	0	0	0

Table B.4. S4 Results

model	L1_Players	L1_Profit	L2_Profit	FEU_LA	FEU_Nk	PR_LA	PR_Nk	RR	PC
0	OC	104,536,000	29,657,600	12,800	51,200	300	300	2,280	220
1	OC P1	106,524,000	27,737,600	12,800	51,200	0	300	2,280	220
2	OC P2	112,472,000	21,977,600	12,800	51,200	300	0	2,280	220
3	OC PC	108,840,000	26,585,600	12,800	51,200	300	300	2,280	0
4	OC R	121,521,600	12,672,000	12,800	51,200	300	300	0	220
5	OC P1 P2	114,460,000	20,057,600	12,800	51,200	0	0	2,280	220
6	OC P1 Pc	110,828,000	24,665,600	12,800	51,200	0	300	2,280	0
7	OC P1 R	123,509,600	10,752,000	12,800	51,200	0	300	0	220
8	OC P2 PC	116,792,000	18,905,600	12,800	51,200	300	0	2,280	0
9	OC P2 R	129,457,600	4,992,000	12,800	51,200	300	0	0	220
10	OC PC R	125,825,600	9,600,000	12,800	51,200	300	300	0	0
11	OC P1 P2 PC	118,780,000	16,985,600	12,800	51,200	0	0	2,280	0
12	OC P1 P2 R	131,445,600	3,072,000	12,800	51,200	0	0	0	220
13	OC P1 PC R	127,813,600	7,680,000	12,800	51,200	0	300	0	0
14	OC P2 PC R	133,777,600	1,920,000	12,800	51,200	300	0	0	0
15	OC P1 P2 PC R	135,765,600	0	12,800	51,200	0	0	0	0

APPENDIX C. FOLLOWING GAME RESULTS

Table C.1. Model Results for {OC, P1, R} in S1

model	L1_Players	L1_Profit	L2_Profit	FEU_LA	FEU_Nk	PR_LA	PR_Nk	RR	PC
0	OC	35,544,000	94,528,000	64,000	0	300	225	2,280	191
1	OC P1	45,484,000	84,928,000	64,000	0	0	225	2,280	196
4	OC R	120,472,000	9,600,000	64,000	0	300	150	0	162
7	OC P1 R	130,412,000	0	64,000	0	0	225	0	218

Table C.2. Model Results for {OC, P1, R} in S2

model	L1_Players	L1_Profit	L2_Profit	FEU_LA	FEU_Nk	PR_LA	PR_Nk	RR	PC
0	OC	25,880,000	94,528,000	64,000	0	300	299	2,280	188
1	OC P1	35,820,000	84,928,000	64,000	0	0	151	2,280	190
4	OC R	110,808,000	9,600,000	64,000	0	300	225	0	189
7	OC P1 R	120,748,000	0	64,000	0	0	298	0	163

Table C.3. Model Results for {OC, P2, PC} in S1

model	L1_Players	L1_Profit	L2_Profit	FEU_LA	FEU_Nk	PR_LA	PR_Nk	RR	PC
0	OC	109,840,000	13,440,000	0	64,000	220	300	1,613	220
2	OC P2	119,840,000	3,840,000	0	64,000	266	0	1,462	220
3	OC PC	115,320,000	9,600,000	0	64,000	268	300	2,143	0
8	OC P2 PC	125,320,000	0	0	64,000	225	0	1,608	0

Table C.4. Model Results for {OC, P2, PC} in S2

model	L1_Players	L1_Profit	L2_Profit	FEU_LA	FEU_Nk	PR_LA	PR_Nk	RR	PC
0	OC	124,200,000	13,440,000	0	64,000	283	300	1,618	220
2	OC P2	134,120,000	3,840,000	0	64,000	225	0	1,232	220
3	OC PC	129,580,000	9,600,000	0	64,000	224	300	1,479	0
8	OC P2 PC	139,520,000	0	0	64,000	223	0	1,130	0

Table C.5. Model Results for {OC, P2, PC} with No Cooperating Benefit in S1

model	L1_Players	L1_Profit	L2_Profit	FEU_LA	FEU_Nk	PR_LA	PR_Nk	RR	PC
0	OC	109,840,000	13,440,000	0	64,000	220	300	1,613	220
2	OC P2	119,440,000	3,840,000	0	64,000	150	0	1,616	220
3	OC PC	113,680,000	9,600,000	0	64,000	224	300	2,222	0
8	OC P2 PC	123,280,000	0	0	64,000	224	0	1,612	0
base	OC P2 PC	125,320,000	0	0	64,000	225	0	1,608	0